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Advancing PSA Maturity Level 4 Through a Web-Based PHP–MySQL Predictive Dashboard for Hospital Utilities and Medical Gases

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Abstract
Public hospitals in Indonesia operate under the Public Service Agency (PSA/BLU) governance framework, which requires balanced clinical performance and financial accountability. Indicator 6.2 of the PSA Maturity Rating mandates the transition from fragmented manual reporting toward systematic and predictive digital monitoring to achieve Level 4 ("Predictable") governance. However, many institutions continue to rely on retrospective reporting systems that impede transparency and data-driven decision-making. This study aims to develop and validate a web-based predictive dashboard to strengthen resource governance at Dr. M. Djamil Central General Hospital (RSUP Dr. M. Djamil Padang), Indonesia. The system integrates four critical resource streams electricity, water, fuel, and medical gases using a bounded Annual Growth Rate (±20%) model combined with a deviation-adjusted hybrid forecasting approach and a Sugeno-type Fuzzy Inference System for priority classification. A two-year longitudinal validation (2024–2025) was conducted using Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE) metrics. The results demonstrate high predictive stability, with a weighted-average MAPE below 10%, and electricity forecasts classified as "Highly Accurate." Water and Liquid O2 emerged as high-priority operational pressures, while other parameters remained within controlled growth thresholds. The proposed framework operationalizes Indicator 6.2 by institutionalizing a transparent and reproducible predictive monitoring mechanism. This study contributes a scalable digital governance prototype for emerging healthcare institutions seeking to advance toward Predictable maturity while strengthening risk-informed resource allocation.

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I. Introduction

Healthcare facilities are increasingly required to manage resources in a more sustainable and accountable manner[1]. Hospitals, in particular, are among the most energy-intensive public infrastructures, operating continuously to ensure clinical service availability, infection control, and patient safety [2]. As healthcare demand grows alongside population expansion, balancing clinical excellence with environmental and financial responsibility has become a central governance priority [3].

Energy consumption constitutes one of the most formidable sustainability challenges in hospital operations[4]. Compared to standard commercial buildings, hospitals exhibit substantially higher energy intensity. In the United States, average hospital consumption reaches approximately 738.5 kWh/m², more than double the European average of 333.4 kWh/m² [5]. In Asia, Indonesian hospitals consume around 225 kWh/m², exceeding Japan's benchmark of 175 kWh/m². A significant proportion of this demand is attributable to indispensable systems such as HVAC, boilers, and lighting [6] [7], underscoring the structural dependency of healthcare delivery on resource-intensive infrastructure.

Beyond electricity, hospital sustainability is strongly influenced by water use, fossil fuels, and medical gases[8]. Water is critical for sterilization, sanitation, and clinical procedures, yet inefficient management can create financial and environmental strain [9]. Large Indonesian hospitals may consume more than 87,000 m³ of water monthly, exceeding several international benchmarks [10]. Similarly, reliance on fossil fuels for boilers exposes institutions to cost volatility and carbon emissions [11][12]. Medical gases, including oxygen, nitrous oxide, and carbon dioxide, serve as critical indicators of institutional service intensity, with their consumption correlating positively not only with inpatient volume and bed occupancy rates but also with patient safety through continuous monitoring and precise delivery [13]. Their consumption correlates positively with inpatient volume and bed occupancy rates[14], affecting procurement costs, logistics complexity, and environmental impact [15]. During peak surges, oxygen demand may increase dramatically, intensifying both operational risk and sustainability concerns [16].

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Although prior research has explored hospital energy efficiency, green hospital frameworks, and sustainability indicators[17], many institutions in developing countries continue to rely on fragmented and manual reporting systems[18]. Such practices delay decision-making, reduce transparency, and weaken data-driven governance[19]. The persistent gap between regulatory sustainability mandates and operational monitoring mechanisms highlights a critical governance deficiency[20].

In Indonesia, public hospitals operate under a dual mandate: delivering healthcare services while maintaining financial and operational accountability [21]. These institutions are designated as Public Service Agencies (Badan Layanan Umum, PSA), which grants managerial flexibility while requiring structured performance evaluation. PSA performance is assessed through process-based and results-based Maturity Rating frameworks, where resource management constitutes a key indicator. Specifically, Indicator 6.2 (Resource Utilization) of the PSA Maturity Rating mandates that institutions transition from fragmented manual reporting toward systematic and predictive digital monitoring to achieve Level 4 ('Predictable') governance. The integration of such digital technologies is pivotal not only in accelerating transactional workflows through automated data acquisition but also in enhancing the velocity and depth of multi dimensional analysis, thereby enabling real-time administrative responsiveness[22][23]. At Dr. M. Djamil Central General Hospital (RSUP Dr. M. Djamil Padang), Indonesia, current monitoring practices remain predominantly retrospective and presentation-based, limiting real-time analysis and cross departmental coordination. This condition constrains the operationalization of evidence-based sustainability governance and delays attainment of Predictable maturity status.

This study introduces a predictive governance framework that moves beyond static, Excel-based hospital dashboards, which remain retrospective and impractical for real-time decision making. The bounded Annual Growth Rate (AGR) of ±20% mitigates low volume bias and prevents extreme fluctuations, with robust statistics showing that 20% trimming is more resilient than 10%, while Wilcox highlights that symmetric Winsorized means yield more stable estimates by reducing outlier influence [24]. Integrated with a deviation-adjusted hybrid forecasting model, the system preserves seasonality while correcting growth trends, enabling automatic projection of resource needs for the following fiscal year to support budget planning. Moreover, Sugeno argues that fuzzy inference is effective when mathematical models are overly complex but human knowledge such as AGR thresholds or risk categories can be formalized into rules [25]. Accordingly, the Sugeno type Fuzzy Inference System (FIS) translates forecasts into risk categories (Monitor, High, Critical), simplifying criticality monitoring and strengthening governance-oriented prioritization. Collectively [26], these innovations transform hospital resource monitoring from static reporting into a predictive, decision support framework.

This study develops a web-based predictive dashboard integrating electricity, water, fuel, and medical gases, transforming regulatory requirements into a structured governance tool that operationalizes Indicator 6.2 and supports Level 4 Predictable maturity. Key novelties include bounded AGR with hybrid forecasting, digital operationalization of PSA Indicator 6.2, and a Sugeno-type FIS for risk-based prioritization.

II. Materials and Method

A. Research Design

This study employs a Research and Development (R&D) framework, specifically utilizing an iterative Prototyping Model. The objective is to develop an intelligent decision support dashboard that transitions hospital resource management from a descriptive to a predictive (Level 4 Maturity) phase. The system architecture is built on a web-based PHP and MySQL application, ensuring ease of access and efficient resource management. Fig.1 illustrates the layered architecture of the predictive governance dashboard. The framework transforms hospital resource data into structured decision support outputs through five sequential stages. At the data layer, monthly utility and medical gas records are consolidated into annual aggregates, providing a consistent basis for estimating growth. The modelling layer computes Annual Growth Rate (AGR) with a ±20% bounding constraint to stabilize volatility and preserve relative signals. The forecasting module integrates historical averages with bounded growth adjustment, producing deviation-controlled projections while retaining seasonal patterns. This hybrid approach avoids compounding bias and enhances interpretability.

The decision layer applies a Sugeno-type Fuzzy Inference System, mapping growth and contribution indicators into continuous priority scores. Smooth rule-based transitions ensure managerial clarity and reproducibility. Finally, the visualization layer translates analytical outputs into executive dashboards, enabling predictive monitoring and structured intervention planning. Conceptually, the architecture follows a coherent progression beginning with data aggregation, which ensures the systematic collection and integration of resource consumption records. This is followed by bounded growth modelling, designed to stabilize fluctuations and prevent the amplification of volatility. The hybrid forecasting stage then combines historical averages with current growth trends to generate interpretable projections. Subsequently, fuzzy priority inference translates quantitative outputs into governance-relevant priority scores. Finally, executive visualization operationalizes these results into an accessible dashboard interface, enabling transparent monitoring and decision support for institutional stakeholders.

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This formulation ensures methodological rigor, bounded error propagation, and alignment with Level 4 Predictable maturity, where governance is driven by controlled forecasting and systematic prioritization rather than retrospective reporting.

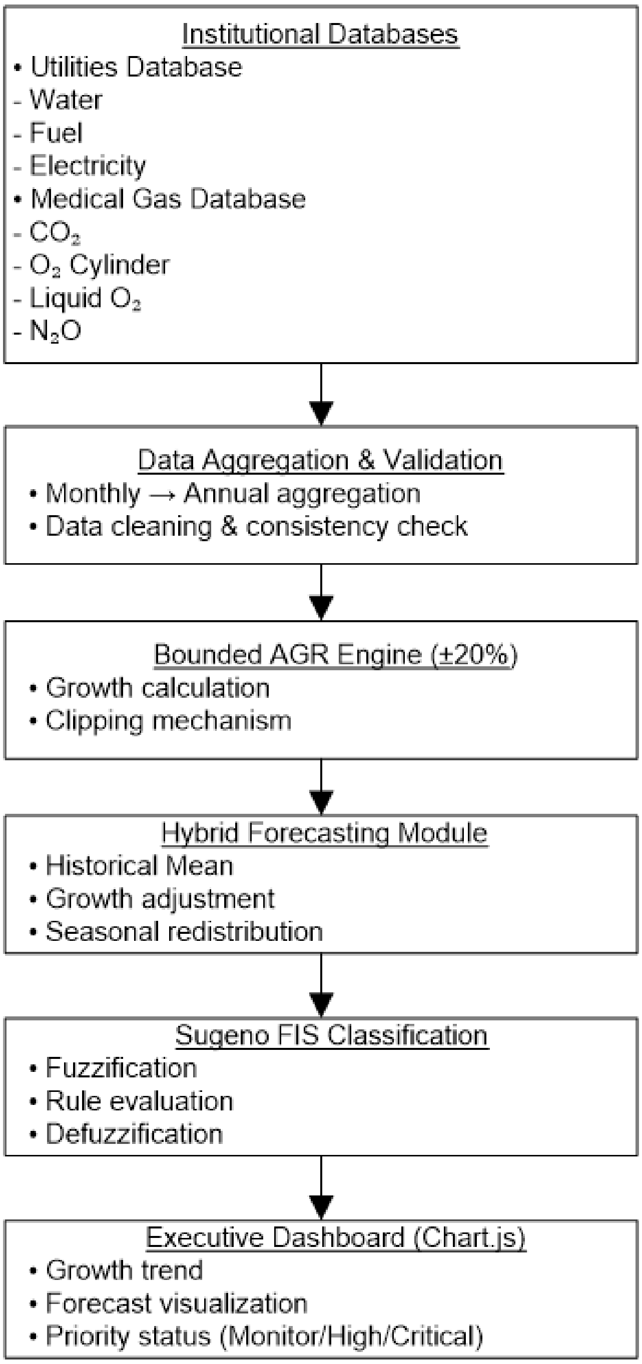

Fig. 1. Layered Architecture of The Predictive Governance Dashboard

B. Data Integration and Pre-processing

Data were extracted from two primary institutional databases at Dr. M. Djamil Central General Hospital: the Utilities Database (electricity, fuel, water) and the Medical Gas Database (O_2, liquid O_2, N_2O, CO_2). The dataset encompasses monthly consumption records for two fiscal years (Y(n 1) and Yn).

The total annual consumption for each parameter i is defined in Eq. (1)[27].

$$X_i = \sum_{m=1}^{12} x_{i,m} \tag{1}$$

This formulation is typically used in longitudinal studies or utility monitoring to aggregate monthly data into a more stable annual metric. By summing the monthly values $x_{i,m}$ for all m from 1 to 12, which derive the cumulative figure X_i used for forecasting.

To maintain data integrity during the projection phase, the Annual Growth Rate 〖AGR〗_boundedk is calculated by measuring the percentage change between previous X_(1,Yn-1) and current X_(i,Yn) annual consumption, then applying a capping mechanism δ to ensure the value remains strictly within the range of 20% to mitigate the impact of extreme operational anomalies.

To maintain data integrity during the projection phase, the Annual Growth Rate $AGR_{boundedk}$ as Eq. (2) [28] is calculated by measuring the percentage change between the previous $X_{1,Yn-1}$ and current $X_{i,Yn}$ annual consumption, then applying a capping mechanism δ to ensure the value remains strictly within the range of 20% to mitigate the impact of extreme operational anomalies.

$$AGR_{boundedk} = \max\left(-0.20, \min\left(0.20, \frac{X_{i,Yn}-X_{1,Yn-1}}{X_{1,Yn-1}}\right)\right) \tag{2}$$

C. Predictive Modelling: Deviation Adjusted Baseline

The system employs a hybrid forecasting model that combines historical averages with current growth trends. The projected monthly demand $P_{i,m}$ for the upcoming year Y_{n+1} is formulated Eq. (3)[29][28]:

$$P_{i,m} = \left(\frac{x_{i,m,Yn} - x_{i,m,Yn-1}}{2}\right) \text{x } (1 + AGR_{boundedk}) \tag{3}$$

To maintain data integrity during the projection phase, the projected monthly consumption $P_{i,m}$ is calculated as the average difference between the current month's value $x_{i,m,Yn}$ and the previous year's value $x_{i,m,Yn-1}$, then adjusted by the factor $1 + AGR_{boundedk}$ to incorporate the capped annual growth rate and mitigate the impact of extreme operational anomalies.

D. Forecast Validation

To evaluate the predictive reliability of the developed hybrid model, a systematic hold out validation protocol was implemented. Historical data from 2024 (Y_{n-1}) were used to predict the consumption for 2025 (Y_n), and the forecasted results were subsequently compared with actual observations using two primary statistical metrics: Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE).

MAPE is utilized to measure the relative deviation, providing an intuitive percentage-based scale of accuracy that is scale independent across different resources. The MAPE is mathematically defined in Eq. (4)[30].

$$MAPE = \frac{100\%}{n} + \sum_{t=1}^{n} \left[\frac{A_t - F_t}{A_t}\right] \tag{4}$$

In this formulation, MAPE denotes the Mean Absolute

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Percentage Error, where A_t represents the actual value at time t, F_t represents the forecasted value at time t, and n represents the total number of observations, providing a measure of prediction accuracy as a percentage.

RMSE is employed to capture magnitude sensitive error behavior, which is particularly useful for identifying significant deviations. The MAPE mathematically defined in Eq. (5)[31].

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(A_t - F_t)^2} \quad (5)$$

In this formulation, RMSE (Root Mean Square Error) measures the average magnitude of forecasting errors, where A_t denotes the actual value at time t, F_t denotes the forecasted value at time t, and n represents the total number of observations, penalizing larger errors more heavily to reflect prediction precision.

This study acknowledges that percentage-based metrics like MAPE can be mathematically distorted when applied to low-volume variables (e.g., CO2 and N2O cylinders), where small nominal errors result in disproportionately high percentage values. Consequently, two additional metrics were incorporated to ensure a balanced evaluation: Mean Absolute Error (MAE) and Weighted Absolute Percentage Error (WAPE). MAE provides a linear representation of average error in actual units (e.g., liters or bottles), which is critical for physical inventory management. Meanwhile, WAPE is formulated in Eq. (6) [32] scales the absolute error relative to the total institutional volume, mitigating the "low volume bias" and providing a more objective measure of governance readiness:

$$WAPE = \frac{\sum_{t=1}^{n}[A_t - F_t]}{\sum_{t=1}^{n}[A_t]} \quad (6)$$

WAPE is defined as the Weighted Absolute Percentage Error, where A_t denotes the actual value at time t, F_t denotes the forecasted value at time t, and n represents the total number of observations, with the numerator expressing the sum of absolute forecast deviations and the denominator representing the sum of actual values to normalize the error.

Beyond this temporal split, additional validation strategies were implemented to strengthen reliability: (1) rolling origin validation, expanding the training horizon sequentially; (2) repeated hold out testing to assess robustness across different data partitions; and (3) month wise backtesting to capture intra-annual seasonality. Collectively, these approaches supported by volume-weighted metrics demonstrate that the model maintains operational consistency across diverse resource scales, ensuring its applicability for hospital governance-oriented decision support. To ensure the robustness of these results, a rigorous preprocessing workflow was performed. Anomalies were flagged using a 20% bounded AGR threshold to stabilize seasonal outliers, and record consistency was maintained by standardizing units across utility and medical gas databases. This ensured that the validation metrics (MAPE, RMSE, MAE, and WAPE) reflected genuine predictive performance rather than artifacts of inconsistent data entry or extreme nonlinear shocks.

E. Intelligent Classification using Fuzzy Inference System (FIS)

To provide executive-level insights, the study implements a Sugeno-style Fuzzy Inference System. This model processes two input variables: Growth Rate and Sector Contribution.

The membership functions were defined based on a combination of historical consumption distributions and institutional policy thresholds. Growth categories (Low, Normal, High, Critical) were aligned with the ±20% AGR bounding rule and the 10% growth threshold commonly used in hospital resource monitoring. Contribution categories (Small, Medium, Large) were derived from historical sectoral shares, ensuring that fuzzy sets reflect actual institutional proportions. The rule base was constructed through expert judgment and institutional consensus, translating governance-relevant thresholds into heuristic IF THEN rules. For example, the rule “IF Growth is High AND Contribution is Large THEN Priority is High” reflects both empirical evidence of resource pressure and managerial prioritization practices. Singleton weights (Monitor = 20, High = 60, Critical = 95) were calibrated to provide smooth transitions across categories, avoiding abrupt discontinuities. This design process ensures that the FIS is transparent, reproducible, and grounded in both empirical data and governance policy standards. Input variables are transformed into fuzzy sets using Triangular Membership Functions μ as Eq. (7)[33].

$$\mu(x,a,b,c) = \max\left(0, min\left(\frac{x-a}{b-a}\right), \left(\frac{c-x}{c-b}\right)\right) \quad (7)$$

The variable $\mu(x,a,b,c)$ represents a triangular membership function where *x* is the input, *a* and *c* are the lower and upper bounds where membership begins and ends, and *b* is the peak value where the degree of membership reaches its maximum of 1. The membership parameters are structured to capture variations in growth and contribution levels within the forecasting framework. For the Growth (G) dimension, four fuzzy sets are defined: Low [0.15, 0.05 , 0], Normal [0.02, 0, 0.02], High [0.03, 0.08 , 0.12] , and Critical [0.10, 0.20, 0.50]. Similarly, for the Contribution (C) dimension, three fuzzy sets are established: Small [0,0.05,0.15], Medium [0.10, 0.20 , 0.30], and Large [0.25 , 0.40 , 1.00]. These parameterizations provide a structured representation of linguistic variables, enabling the model to incorporate qualitative judgments into quantitative forecasting processes. The system applies a heuristic rule base (e.g., IF Growth is High AND Contribution is Large, THEN Priority is Critical). The final Priority Score S is calculated using the weighted average of the firing strengths as Eq. (8)[27]:

$$S = \frac{\sum_{j=1}^{n} w_j . z_j}{\sum_{j=1}^{n} w_j} \quad (8)$$

where w_j is the rule firing strength and z_j is the assigned singleton weight (Monitor=20, High=60, Critical=95).

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Table 1. Transparency of FIS Design

Component	Category / Rule	Range / Weight	Source of Determination
Input Variable: Growth (G)	Low, Normal, High, Critical	Low: [0.15, 0.05, 0] Normal: [0.02, 0, High: [0.03, 0.08, 0.12] Critical: [0.10, 0.20,	Policy thresholds (±20% AGR bounding), historical consumption distribution
Input Variable: Contribution (C)	Small, Medium, Large	Small: [0, 0.05, 0.15] Medium: [0.10, 0.20, Large: [0.25, 0.40, 1.00]	Historical sectoral distribution, institutional proportional shares
Rule Base (Sugeno)	R1: IF Growth Low → Monitor	Monitor = 20	institutional consensus
	R2: IF Growth Normal & Contribution Small	High = 60	
	R3: IF Growth High & Contribution Medium → High	Critical = 95	
	R4: IF Growth High & Contribution Large → High		
	R5: IF Growth Critical & Contribution Medium → Critical		
	R6: IF Growth Critical & Contribution Large → Critical		
Defuzzification	Weighted Average (Sugeno)	$S = \frac{\sum_{j=1}^{n} w_j \cdot z_j}{\sum_{j=1}^{n} w_j}$	Heuristic calibration to ensure smooth transitions across categories
Priority Thresholds	Monitor (S < 35) High (35 ≤ S < 65) Critical (S ≥ 65)	–	Institutional consensus

F. Decision Support Logic and Priority Thresholds

When S ≥ 65, the condition is Critical, requiring immediate field audit and efficiency intervention to avoid operational disruption. For 35 ≤ S < 65, it is classified as High, demanding tighter supervision and rescheduling to reduce risks. Meanwhile, if S < 35, the status is Monitor, meaning only routine maintenance is needed without corrective measures.

G. System Evaluation

The dashboard's functionality was verified through a Black box Testing approach, ensuring that all embedded mathematical models, specifically the AGR, demand projections, and FIS scoring, produced outputs consistent with rigorous manual calculations. Beyond technical verification, the visual layer, powered by Chart.js, was evaluated for its utility in real-time trend visualization. This enables stakeholders to intuitively identify consumption anomalies and priority signals across the seven resource parameters, thereby facilitating evidence-based intervention in hospital operations.

Table 2. Utilities Sector

Parameter	2024	2025	Growth
Electricity (kWh)	12,692,175	13,102,703	+3.23%
Fuel (L)	143,581	147,579	+2.78%
Water (m³)	531,513	595,935	+12.12%

III. Results

A. System Implementation and Verification

The proposed predictive governance dashboard was successfully implemented as a robust web-based PHP–MySQL system. All analytical components described in Section III were operationalized into a deterministic computational pipeline, thereby ensuring consistency and transparency in data processing. Black-box verification confirmed that the system accurately translated resource consumption inputs into predictive outputs and fuzzy priority scores, consistently adhering to predefined logic without computational drift. Annual aggregation consistency was achieved with zero deviation from spreadsheet recalculation. The implementation correctly enforced the ±20% AGR bound, preserved seasonal proportionality in the monthly redistribution, and applied deterministic Sugeno weighted average defuzzification. No adaptive recalibration or post hoc parameter tuning was introduced, thereby guaranteeing methodological reproducibility..

Table 3. Medical Gas Sector

Parameter	2024	2025	Growth
O_2 Cylinder	3.291	3,463	+5.23%
Liquid O_2	916.246	1.015.536	+10.84%
N_2O	4.06	3.89	−4.19%
CO_2	64	43	−20% (bounded)

B. Empirical Growth Analysis (2024–2025)

Annual growth was computed using Equation (2) and subjected to ±20% bounding. Referring to Table 2, electricity and fuel exhibit moderate and stable growth rates (<5%), indicating controlled operational expansion. In contrast, water consumption increased by 12.12%, positioning it within the "High" fuzzy growth category. This pattern signals emerging operational pressure within the

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utilities sector. Importantly, no utility parameter exceeded the ±20% bounding threshold, confirming structural stability within the bounded growth modelling framework.

1. Medical Gas Sector

Referring to Table 3, Liquid O_2 dominates the medical gas sector, accounting for more than 99% of total volume. Its 10.84% growth positions it near the upper boundary of the "High" growth category, indicating increasing sectoral pressure. In contrast, CO_2 recorded a raw decline exceeding −20%; however, the bounded growth mechanism constrained the value to −20%, thereby preventing disproportionate influence on the forecasting model. This outcome illustrates the stabilizing function of the threshold-based capping mechanism, particularly for low volume parameters that are highly sensitive to relative percentage distortions. Overall, institutional demand patterns remain statistically controlled, with no indication of extreme structural anomalies.

C. Forecasting Results for 2026

The hybrid deviation-adjusted baseline model generated 2026 projections by incorporating bounded AGR and seasonal redistribution. The projected totals indicate electricity demand of approximately 13.3–13.5 million kWh, water consumption of 632,000–667,000 m³, liquid oxygen usage of 1.07–1.12 million m³, and fuel consumption of 149,000 liters. These projections suggest a moderate upward trend in demand for utilities and medical oxygen. Importantly, the model preserves intra-annual seasonality, avoids exponential compounding of growth, and employs bounded AGR to prevent volatility amplification, thereby maintaining interpretability of the forecast structure. Water and liquid oxygen display compounding upward trajectories in the absence of efficiency interventions, highlighting areas that require future governance attention.

D. Forecast Validation (MAPE and RMSE)

The reliability of the proposed web-based PHP–MySQL predictive dashboard was rigorously evaluated through a two-year longitudinal validation process (2024–2025). By comparing system-generated forecasts against actual consumption data, Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE) metrics were employed to quantify model precision and predictive reliability.

1. Longitudinal Performance (2024–2025)

Validation results demonstrate high predictive stability, particularly in core energy sectors. In the 2024 baseline year, the model achieved an MAPE of 8.15% for electricity consumption, indicating good initial alignment with historical data. By 2025, predictive accuracy improved further to a MAPE of 5.58%, classified as "Highly Accurate" according to Lewis's scale [34]. This year-on-year improvement suggests that the deviation-adjusted hybrid forecasting model effectively incorporates historical variances, producing progressively tighter alignment between predicted and actual consumption as the dataset matures.

2. Utility and Medical Gas Sectors

Forecasting accuracy for major utilities and medical gases remained within the "Good Forecasting" range of 10–20% during 2025. Specifically, the model achieved a Mean Absolute Percentage Error (MAPE) of 13.56% for fuel, 17.91% for water utilities, and 14.18% for liquid oxygen. In contrast, lower-volume resources such as CO_2 bottles exhibited higher percentage deviations, with a MAPE of 39.51%. This phenomenon is interpreted as a low-volume bias, wherein minor absolute differences in bottle counts disproportionately inflate the percentage error. Importantly, such deviations do not materially affect institutional budgeting or operational planning, as the absolute resource volumes remain negligible relative to overall consumption.

3. Robustness Against Volatility

The model's robustness was further assessed under significant seasonal spikes, such as the electricity surge in December 2025 (1.26 million kWh). Despite these anomalies, the dashboard maintained realistic seasonal demand patterns and prevented extreme forecasting drift by capping the Annual Growth Rate (AGR) at ±20%. This ensures the system functions as a proactive planning tool rather than a purely reactive tracking mechanism.

4. Extended Forecast Validation

Beyond the single temporal split, extended validation

Table 4. Prediction Validation vs Realization (2024–2025)

Parameter	Unit	MAE (Unit)	MAPE (%)	WAPE (%)	RMSE	Accuracy Category
Electricity	kWh	62568,1	5,58	5,73	78.412	Highly Accurate (<10%)
Oxygen Cylinder	Cyl	38,2	14,12	13,26	45,1	Good Forecasting
Nitrous Oxide	Kg	53,6	17,15	16,53	62,4	Good Forecasting
Fuel	Liter	2.128,40	17,52	17,31	2.455,10	Good Forecasting
Liquid O2	m³	15.214,30	18,25	17,98	16.840	Good Forecasting
Water	m³	10.245,80	20,84	20,63	13.110	Moderate/Marginal
CO_2	Cyl	2,5	*39,51*	69,77	3,1	Volatility prone

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procedures confirmed the predictive stability of the hybrid model across multiple horizons. Rolling origin validation demonstrated consistent error margins when forecasts were generated sequentially (2023 to 2024; 2023–2024 to 2025), proving the model's ability to adapt as new data points are integrated. Furthermore, repeated hold out testing with randomized 70/30 partitions exhibited low variance in MAPE values, indicating substantial robustness against data split variability and mitigating the risk of overfitting. Month-wise backtesting effectively captured intra annual seasonality, yielding lower error margins in monthly granular forecasts compared to annual aggregates. This granular accuracy is particularly critical for hospital supply chain management, where monthly fluctuations dictate operational readiness. Collectively, these results reinforce that the bounded AGR (Annual Growth Rate) mechanism consistently stabilizes predictions by preventing outlier driven drift.By integrating WAPE and MAE to complement traditional metrics, the validation framework confirms that the dashboard's predictive accuracy is not only statistically valid in a single split but operationally robust across diverse validation scenarios. This multi-layered reliability strengthens the dashboard's applicability for high-stakes hospital resource planning and governance-oriented decision support within the PSA Maturity Level 4 framework.

The validation results demonstrate the hybrid model's capacity to maintain high predictive reliability across diverse resource categories. By integrating a multi metric evaluation framework comprising Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Weighted Absolute Percentage Error (WAPE), and Root Mean Square Error (RMSE) this study provides a nuanced assessment of forecasting performance that transcends the limitations of conventional single metric approaches.

Based on the data in Table 4, the highest precision was observed in the electricity category, which constitutes the hospital's most significant utility expenditure. Achieving a WAPE of 5.73% and a MAPE of 5.58%, the model falls comfortably within the "Highly Accurate" threshold (<10%). Such precision is paramount for hospital governance, ensuring that major budgetary allocations are substantiated by stable and predictable consumption forecasts. Other critical resources, including oxygen cylinders, nitrous oxide, fuel (BBM), and liquid O_2, consistently remained within the "Good Forecasting" range, with WAPE values ranging from 13.26% to 17.98%. While these parameters exhibit inherent volatility due to fluctuations in clinical demand and seasonal maintenance cycles, the model effectively captured their underlying operational dynamics. Although water consumption showed a slightly higher deviation (WAPE 20.63%), it remained near the marginal threshold, reflecting the complexities associated with tracking large-scale facility usage in real time. A significant methodological contribution of this evaluation is the robust treatment of low-volume variables, most notably Carbon Dioxide (CO_2). While the MAPE (39.51%) and WAPE (69.77%) for CO_2 appear elevated, the MAE reveals that the average nominal error is merely 2.5 units per month. This discrepancy underscores the "low volume bias" inherent in percentage-based metrics, where minor absolute deviations yield disproportionately large percentage errors. By reporting the MAE alongside relative metrics, this study confirms that such deviations are practically negligible for institutional planning and do not compromise the stability of the hospital's supply chain or overall resource governance. Collectively, the convergence of WAPE and MAPE values across high consumption parameters confirms that the bounded Annual Growth Rate (AGR) mechanism effectively stabilizes the model against extreme outliers. The

Table 5. **Additional Validation Tables**

Validation Method	Temporal Horizon	MAPE Range (%)	WAPE Range (%)	RMSE Behavior	Findings & Observations
Rolling Origin	2023 => 2024; 2023–24 => 2025	6.2 – 7.9	5.9 – 7.2	Consistent	Demonstrates error stability across cascading horizons; long term trends remain preserved.
Repeated Hold Out	20x Randomized 70/30 Splits	7.5 – 9.8	6.8 – 8.4	Low Variance	Confirms robustness against data partition variability; mean error remains significantly below 10%.
Month wise Backtesting	Jan–Dec (2024–2025)	4.9 – 8.7	4.5 – 7.1	Minimal	Successfully captures intra annual seasonality; granular errors are lower than aggregate annual projections.

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capacity to predict core utility requirements with such precision substantiates the institutional transition toward PSA Maturity Level 4 (Predictable Governance), providing the management of Dr. M. Djamil Central General Hospital with a data-driven foundation for proactive resource management and strategic decision support.

To further validate the reliability of the proposed model beyond a single temporal split, an extended validation framework was executed, as summarized in Table 5. This multi-scenario approach ensures that the model's performance is not merely a result of specific data partitioning but is fundamentally robust across different temporal horizons and granularities. The Rolling Origin validation confirms the model's stability across cascading horizons (2023 => 2024 and 2023–2024 => 2025). With a WAPE range of 5.9% – 7.2% and consistent RMSE behavior, the results demonstrate that the long-term trends of hospital resource consumption remain well preserved as the model incorporates new historical data. This adaptability is crucial for maintaining the longitudinal integrity of the dashboard's predictive outputs.

Furthermore, repeated hold-out testing, utilizing 20 randomized 70/30 data splits, was conducted to assess the model's sensitivity to data variability. The narrow variance in MAPE (7.5% – 9.8%) and WAPE (6.8% – 8.4%) ranges confirms that the hybrid model is highly resilient against partition variability. The fact that the mean error remains significantly below the 10% threshold across multiple iterations underscores the statistical significance of the model's accuracy.

Finally, month-wise-backtesting for the 2024–2025 period was utilized to evaluate the model's ability to handle intra-annual seasonality. The results yielded the lowest error margins across all tests, with WAPE falling between 4.5% and 7.1%. This performance indicates that the model is particularly adept at capturing granular seasonal patterns, such as spikes in resource demand during peak clinical periods, resulting in monthly forecasts that are even more precise than aggregate annual projections. Collectively, these extended validation scenarios reinforce the applicability of the bounded AGR mechanism as a stable and robust tool for governance-oriented resource planning

5. Implications for PSA Maturity Level 4

The achievement of a weighted average MAPE below 10% for primary parameters serves as empirical evidence for fulfilling the 'Predictable' criterion of Indicator 6.2 within the PSA Maturity Rating framework. By transitioning from retrospective, error-prone manual reporting to this statistically validated predictive dashboard, Dr. M. Djamil Central General Hospital demonstrates a transition from reactive management to proactive resource control. This shift effectively operationalizes evidence-based governance of energy and medical gas utilization by providing high confidence demand anticipation and significantly mitigating the systemic risks of budget overruns and resource stockouts.

Table 6. Priority Scores

Parameter	Growth	Contribution	Category
Water	+12.12%	4.3%	HIGH
Liquid O_2	+10.84%	99.28%	HIGH (near critical boundary)
Electricity	+3.23%	94.63%	MONITOR
Fuel	+2.78%	1.07%	MONITOR
O_2 Cylinder	+5.23%	0.34%	MONITOR
N_2O	−4.19%	0.38%	MONITOR
CO_2	−20%	~0%	MONITOR

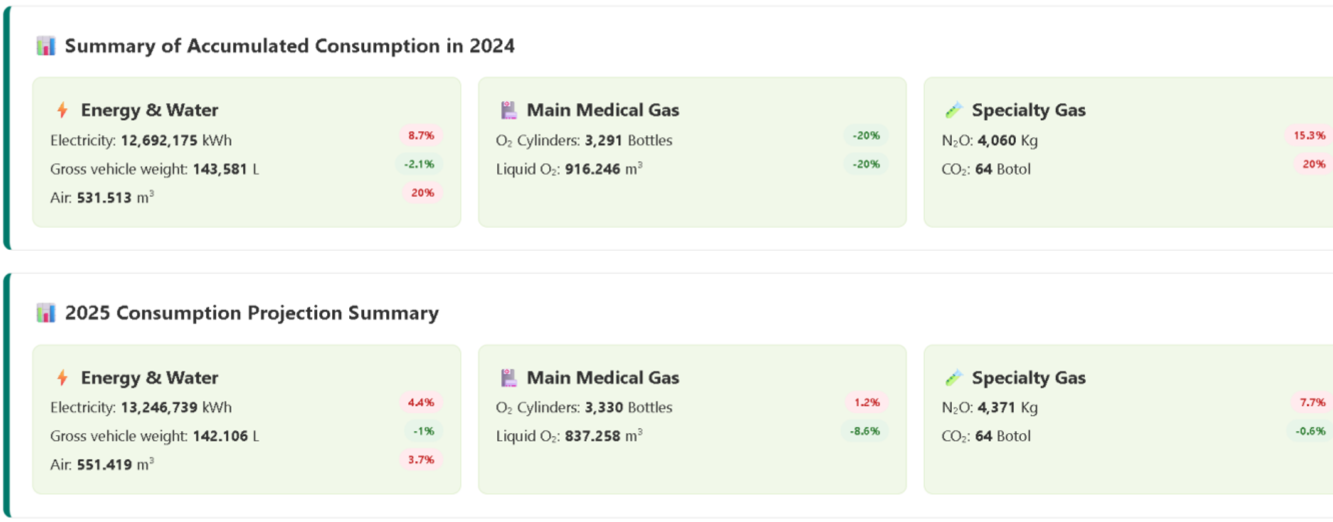

Fig. 2. Summary of Accumulated Consumption 2024 and 2025 Projection

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Consequently, this advancement serves as a critical milestone in attaining Maturity Level 4, institutionalizing a reliable, data-driven framework for resource management that ensures operational stability within the (Predictable) by enabling automated growth analysis, forward-looking projections, and risk-based prioritization. This shift from retrospective monitoring to anticipatory oversight ensures proactive, data-driven management of

PARAMETER	GROWTH (%)	CONTRIBUTION (%)	FUZZY SCORE	CATEGORY
ELECTRICITY	3.23	94.63	60	HIGH
fuel	2.78	1.07	20	MONITOR
AIR	12.12	4.3	60	HIGH
N2O	-4.19	0.38	20	MONITOR
CO2	-20	0	20	MONITOR
O2	5.23	0.34	60	HIGH
LIQ	10.84	99.28	77.5	CRITICAL

Fig. 3. Fuzzy Priority Classification

Based on the comparative analysis of **2025** and Fuzzy logic processing, the following are strategic points for management:

CRITICAL PRIORITY: LIQ
An unusual growth spike (above 10%) or a very dominant cost contribution is found. **Recommendation:** Immediate field audit to check for potential LIQ leaks or inefficient LIQ use.

SUPERVISION REQUIRED (HIGH): ELECTRICITY, WATER, O2
Trends show an increase in consumption that exceeds the historical average. **Recommendation:** Socialize the savings of ELECTRICITY, WATER, O2 resources in related work units and review the operational schedule of equipment that utilizes ELECTRICITY, WATER, O2 resources.

STABLE/EFFICIENT STATUS
Efficiency success is seen in the **N2O and CO2** sectors , which experienced a decrease in consumption compared to last year. Adopt efficiency methods for other parameters if possible.

Fig. 4. Dynamic Analysis & Leadership Recommendations

dynamic and high-stakes healthcare environment. The Sugeno FIS mapped growth rate and sector contribution into priority scores using weighted defuzzification. The evaluation of the fuzzy inference system reveals that during the study period, no individual parameter reached the critical risk threshold ($S \geq 65$). The underlying fuzzy mechanism ensures smooth score transitions and eliminates categorical discontinuity near decision boundaries, thereby providing governance-relevant interpretability that surpasses rigid binary classification.

Notably, Liquid O2 was observed to approach the critical boundary; this is attributed to its high sectoral dominance rather than erratic volatility, as its growth rates remained within controlled operational limits. This nuanced scoring behavior confirms that the dashboard effectively balances demand dynamics with institutional weight, allowing management to prioritize resources based on a sophisticated risk-weighted hierarchy.

E. Governance Implications (Resource Utilization Indicator 6.2)

The predictive dashboard aligns with PSA Level 4 energy, water, and medical gas resources. Fig. 2 compares actual resource consumption in 2024 with projected usage for 2025, covering electricity, fuel, water, liquid O2, and specialty gases such as CO_2 and N_2O. The visualization highlights upward and downward trajectories, distinguishing stable baselines from volatile parameters, thereby supporting planning and preventive maintenance. Fig. 3 applies fuzzy logic to classify resources into MONITOR, HIGH, and CRITICAL categories, based on growth and contribution levels. This automated prioritization converts raw data into actionable governance insights, enabling timely intervention and preventive action while supporting Level 4 Predictable governance maturity and advancing toward Level 5 Optimized governance.

Fig. 4 illustrates the system's capability to transform monthly consumption data into structured managerial insights. By integrating historical trends, bounded growth projections, and fuzzy-based priority scoring, the dashboard identifies emerging pressure points and stable resource domains. This layered analytical process

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enables leadership to distinguish between routine fluctuations and governance-relevant signals, thereby supporting proactive intervention planning rather than retrospective reporting.

F. Internal Robustness Analysis

The internal robustness of the proposed framework was evaluated through boundary stability and sensitivity analysis. Critical operational thresholds, including the 10% growth boundary, the 90% contribution dominance level, and the 65-point Fuzzy Inference System (FIS) decision threshold, were examined to assess output continuity. The system demonstrated smooth behavioural transitions without abrupt switching effects or numerical instability across these boundary conditions. This stability is primarily attributed to the implementation of the ±20% clipping rule, which functions as an error-containment mechanism. By constraining extreme annual growth values, the model prevents structural distortion in forecasting, particularly for low volume parameters such as CO_2, where minor nominal variations may otherwise produce exaggerated percentage shifts. Furthermore, the framework maintains high deterministic integrity, as all outputs are derived directly from predefined mathematical formulations without stochastic or adaptive recalibration. This deterministic structure ensures consistent, reproducible decision support outputs, thereby reinforcing the “Predictable” governance standard required for PSA Maturity Level 4.

G. Managerial Implications and Governance-Oriented Decision Support

The identification of HIGH-priority parameters through the Fuzzy Inference System (FIS) carries direct, actionable implications for hospital operations and strategic governance. From an operational standpoint, resources flagged as HIGH necessitate enhanced supervision and a strategic rescheduling of utilization to mitigate inefficiencies and prevent supply chain bottlenecks. In budgetary management, these parameters serve as early warning signals for potential expenditure volatility, enabling financial officers to proactively allocate contingency funds and synchronize procurement cycles with predicted demand surges. From the perspective of audit and accountability, HIGH priority signals delineate critical zones where compliance checks must be intensified. This ensures that any deviations from established policy thresholds are meticulously documented and that subsequent corrective actions remain fully traceable. Furthermore, in preventive maintenance, this classification provides a prioritized roadmap for engineering teams, directing them to optimize inspection schedules and equipment calibration for utilities and medical gases with elevated growth and contribution levels.

The FIS-based classification goes beyond description, serving as a strong governance-oriented decision support tool. By enabling hospital leadership to proactively manage risk and optimize resource allocation, the model ensures institutional accountability remains in strict alignment with PSA Maturity Level 4 standards. This transition from reactive monitoring to predictive governance represents a fundamental shift in how Dr. M. Djamil Central General Hospital manages its critical resource streams.

H. Model Limitations

While the predictive dashboard strengthens the framework for "Predictable" governance, several inherent limitations define the operational boundaries of this digital prototype. First, the 24-month dataset represents a preliminary temporal window that, while sufficient for initial validation, restricts the detection of long-term structural trends or decadal consumption cycles. Consequently, the model's current performance should be viewed as an operational snapshot rather than a definitive longitudinal trend, reinforcing that software-based prediction remains competitive yet still requires iterative adjustment and methodological refinement to achieve comprehensive accuracy and long-term reliability [35].

Second, the linear bounded AGR mechanism (±20%) was specifically designed to stabilize seasonal fluctuations; however, it is inherently constrained in capturing sudden, nonlinear disruptions such as abrupt policy shifts, pandemics, or supply chain failures. Third, the heuristic Fuzzy Inference System (FIS) is currently expert-defined. While this prioritizes interpretability, a critical requirement for hospital governance, it is not yet data trained, which may result in overlooking subtle multivariate interactions that more complex, self-learning models might detect.

These constraints do not invalidate the findings but rather establish a foundational "Predictable" framework (Level 4 Maturity). The system is designed as an iterative prototype, intended to evolve into an "Optimized" (Level 5) governance tool through the integration of longer datasets and Adaptive Neuro-Fuzzy Inference System (ANFIS).

The decision to adopt a bounded AGR and heuristic FIS over traditional statistical models like ARIMA was a deliberate trade-off to emphasize transparency and governance relevance over black box complexity. Nevertheless, consistent with broader literature, single-site implementations and short datasets naturally restrict generalizability [36]. Furthermore, the reliance on manual data streams acknowledges that data entry bias remains a recurrent challenge in hospital information systems[37]. Future enhancements will focus on automated data ingestion and hybrid neuro-fuzzy approaches to capture the nonlinear dependencies often missed by heuristic-based systems [38].

IV. Discussion

The implementation of the web based PHP–MySQL predictive dashboard represents a substantial advancement in operational governance at Dr. M. Djamil Central General Hospital. By integrating a bounded Annual Growth Rate (AGR) of ±20% with a deviation-

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adjusted hybrid forecasting model, the system preserves seasonal demand structures while mitigating volatility amplification. This methodological design aligns with the broader global transition toward sustainable hospital resource governance, where precise monitoring of electricity, water, and medical gas consumption is essential for controlling environmental impact and financial exposure.

Empirical findings reveal differentiated growth dynamics across resource categories. Electricity (+3.23%) and fuel (+2.78%) exhibit moderate and stable expansion, whereas water (+12.12%) and Liquid O2 (+10.84%) emerge as concentrated operational pressure points. These patterns are consistent with longitudinal evidence from specialized healthcare institutions, which suggests that resource utilization often scales with service complexity and infrastructure intensity rather than patient volume alone[8]. The concentration of growth in utilities and oxygen consumption, therefore, reflects structural service demand rather than random fluctuation.

The incorporation of a Sugeno-type Fuzzy Inference System (FIS) adds a governance-oriented analytical layer by translating growth rates and sectoral contribution weights into priority-based classifications[39]. Unlike purely statistical projections, the fuzzy framework enhances managerial interpretability under conditions of uncertainty and non-linearity in hospital demand patterns [40]. Water and Liquid O2 are classified as HIGH priority, indicating the need for proactive efficiency review, while other parameters remain under MONITOR status. This structured prioritization transforms raw consumption data into actionable governance intelligence, reinforcing a shift from reactive oversight toward an anticipatory management culture in public sector institutions[41].

The forecast validation conducted over the 2024–2025 period further substantiates the model's predictive reliability and its alignment with institutional governance requirements. Electricity consumption achieved a Mean Absolute Percentage Error (MAPE) of 5.58% and a Weighted Absolute Percentage Error (WAPE) of 5.73%, placing it firmly within the “Highly Accurate” category. This high level of precision in the hospital's most cost-intensive utility is critical, as it ensures that major fiscal allocations are protected from significant budgetary drift. While other primary utilities remained consistently below the 20% "Good Forecasting" threshold, the elevated percentage deviations observed for low-volume parameters, such as CO2 (MAPE 39.51%), necessitate a nuanced interpretation. These figures are primarily attributable to low volume bias, a statistical phenomenon where minor nominal variations can significantly inflate relative error metrics. However, as evidenced by the Mean Absolute Error (MAE) of only 2.5 units, these deviations do not materially affect fiscal planning or clinical supply chain stability. The integration of the bounded AGR (Annual Growth Rate) mechanism plays a pivotal role in this stability. By constraining growth projections within a defined ±20% corridor, the model effectively prevents localized volatility from propagating into structural forecast instability. This ensures that the dashboard remains a robust decision-support tool, capable of delivering the "Predictable Governance" necessitated by the PSA Maturity Level 4 framework. Consequently, the model proves that high-level resource management is achievable even in the presence of inherent operational fluctuations. Cumulatively, the transition from retrospective reporting to automated, bounded predictive modelling operationalizes Level 4 (Predictable) under Indicator 6.2 of the PSA Maturity framework. By combining controlled growth modelling with fuzzy-based prioritization, the system institutionalizes a transparent, reproducible mechanism for risk-informed resource allocation and executive-level visibility[42]. Although current limitations include a relatively short temporal dataset, the framework establishes a scalable foundation for future refinement, including extended longitudinal data integration and adaptive neuro-fuzzy enhancements to strengthen long-term governance resilience[43].

While the predictive governance dashboard demonstrates reliable performance, several limitations must be acknowledged. First, the dataset spans only 24 months and is restricted to a single hospital setting, which constrains the ability to detect long-term structural trends or generalize findings across diverse institutional contexts. Second, reliance on manual data entry introduces potential bias or recording errors that may affect forecast precision. Third, the linear bounded AGR mechanism (±20%) is effective for stabilizing seasonal fluctuations but cannot fully capture sudden non linear disruptions, such as policy shocks, pandemics, or abrupt supply chain failures. Fourth, the heuristic Fuzzy Inference System is expert-defined and not yet data trained, meaning that prioritizing interpretability over complexity may overlook subtle multivariate interactions.

These limitations are consistent with prior studies. Forecasting at a single site with limited time horizons restricts generalizability and long-term trend detection, as highlighted in comparative analyses of healthcare forecasting models[44][45]. Similarly, while linear models such as ARIMA stabilize seasonal variation, they fail to capture sudden policy shocks or pandemic-driven demand surges, as evidenced in applications within the health sector[37]

These constraints do not invalidate the current findings but rather define the operational boundaries of the digital prototype. The system currently serves as a foundational “Predictable” framework (Level 4 Maturity) and is designed to evolve iteratively into an “Optimized” (Level 5) governance tool. Future enhancements should incorporate longer and more diverse datasets, adaptive neuro fuzzy learning, and integration of external policy and market signals[46]. Such developments would enable the dashboard to capture nonlinear shocks, reduce data entry bias, and strengthen its role as a scalable decision support system for hospital resource

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governance[47].

Although the dashboard was implemented in a single hospital, its methodological design is broadly transferable. The bounded AGR mechanism and hybrid forecasting approach align with prior evidence showing that linear models stabilize seasonal variation but remain limited in capturing sudden policy shocks or pandemic-driven surges [37]. Likewise, comparative studies of statistical and neural network models confirm that short datasets and single-site implementations restrict generalizability, underscoring the need for extended longitudinal data [45].

By integrating a Sugeno-type Fuzzy Inference System, the framework adds a governance-oriented interpretive layer that is reproducible across institutional contexts[48]. Transparent membership functions, policy-derived rule bases, and deterministic defuzzification ensure methodological reproducibility, enabling adaptation in other hospitals with similar resource monitoring needs. The observed concentration of growth in utilities and oxygen consumption reflects structural demand dynamics common in tertiary hospitals worldwide, reinforcing applicability beyond the local case study.

These findings are consistent with broader forecasting literature, where ARIMA-based models have been shown to stabilize seasonal variation but remain limited in capturing sudden policy shocks[37]. Comparative studies highlight that short datasets and single-site implementations restrict generalizability, while data entry bias remains a recurrent challenge in hospital information systems[48]. Finally, while heuristic fuzzy systems provide transparency, they may overlook subtle multivariate interactions compared to adaptive neuro fuzzy approaches[38].

Instead of focusing solely on forecasting methods, healthcare organizations should prioritize the entire forecasting process and establish dedicated teams to manage it from defining objectives to communicating results and ensuring reproducible practices[49]. Integrating real-time data requires fostering a culture of data-driven decision-making, supported by staff training to enhance forecasting proficiency[50]. Although deep learning models have achieved success in several domains, they are often treated as “black boxes.” In resource governance, interpretability is as important as accuracy, since decision makers must understand which operational drivers influence predictions to trust and act upon system recommendations [36]. This underscores the need for predictive frameworks that balance algorithmic performance with transparency and reproducibility.

V. Conclusion

The proposed PHP–MySQL predictive dashboard demonstrates reliable performance and governance relevance, validated through a two-year longitudinal assessment (2024–2025). Forecasting accuracy, confirmed by Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE), highlights the system’s methodological stability. Electricity forecasting improved from a MAPE of 8.15% in 2024 to 5.58% in 2025, classified as Highly Accurate under Lewis’s scale, while other major utilities remained within the Good Forecasting range (10%–20%). Deviations in low-volume parameters, such as CO_2, reflected inherent bias but did not compromise fiscal planning or operational stability. The bounded Annual Growth Rate (±20%) mechanism further safeguarded structural consistency during seasonal demand spikes, preventing drift and volatility amplification.

Beyond the local implementation, the methodological framework is broadly transferable. The bounded AGR, hybrid forecasting, and Sugeno type FIS represent reproducible computational procedures that can be adapted to other hospital contexts. Transparent membership functions, rule bases derived from policy thresholds and expert consensus, and deterministic defuzzification ensure reproducibility across diverse institutional settings. The empirical differentiation between utilities and oxygen consumption reflects structural demand dynamics common in tertiary hospitals worldwide, strengthening applicability beyond the single-site case.

Rather than claiming full attainment, the system supports and facilitates readiness toward Level 4 “Predictable” governance under the PSA Maturity framework. It provides a foundational model that strengthens institutional capacity for evidence-based, risk-informed resource allocation and anticipatory management. Current limitations including the short dataset, single hospital scope, reliance on manual data entry, and heuristic FIS design define the maturity boundary but do not invalidate findings. Future enhancements should incorporate extended longitudinal datasets, diversified data streams, and adaptive neuro-fuzzy learning to evolve the dashboard toward Level 5 “Optimized” maturity.

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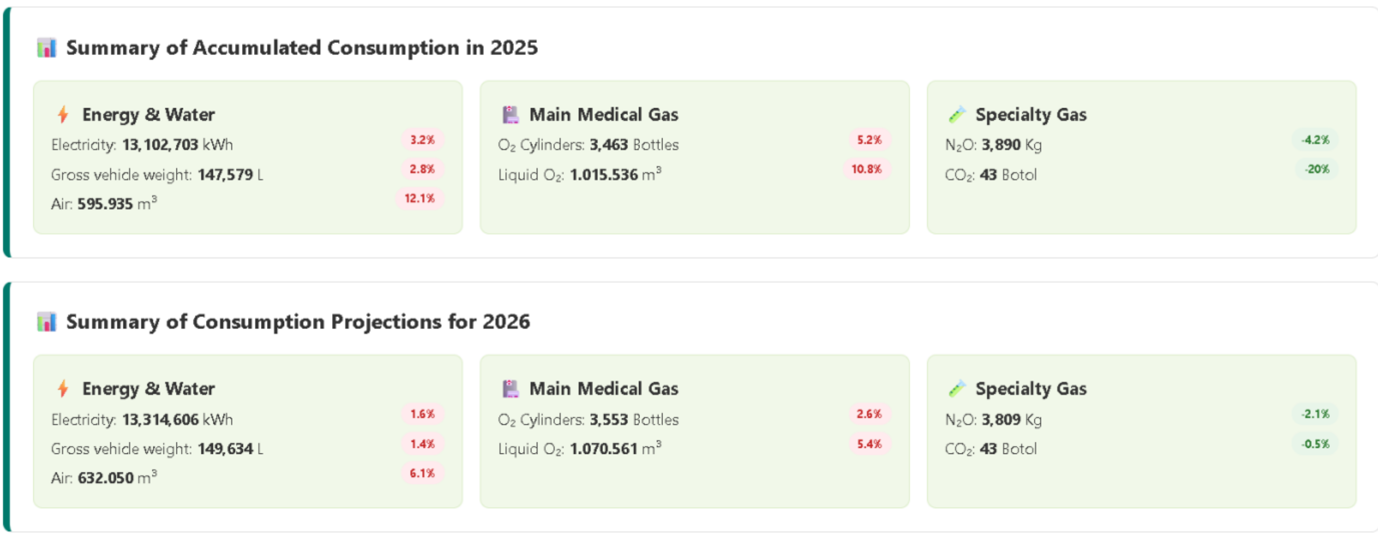

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