

A Layered Framework for AI-Managed Power and Industrial Systems

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Abstract

Predictive resilience modelling underpins operational continuity in industrial and power generation infrastructures. These systems can sustain stable operation under a range of disruptions because the likelihood of the most foreseeable failure modes is continuously monitored and, where necessary, mitigated before it materializes.

Two complementary models clarify the discussion of AI-governed resilience. The first, a data architecture layer, focuses on resilience-enhancing feature engineering — identifying and structuring the data signals most relevant to anticipating risk. The second, a multilayer predictive model, monitors key risk drivers across layers, with each layer designed to detect and avert specific, predictable operational breaches or failures.

AI-governed control operates at a further level: it determines the minimum degree of automated intervention and external oversight needed to preserve operational resilience. Predictive models define the decision boundaries of operational stability — the range within which internal and external shocks remain manageable and do not threaten system integrity. As long as operations remain within these boundaries, automated actions do not compromise the reliability of the broader safety and control system; instead, they support the operability, responsiveness, and continuity of all other planned interventions, while remaining as minimally intrusive as possible.

Keywords: IPredictive Resilience Modelling, AI-Governed Control Systems, Operational Continuity Management, Multilayer Predictive Monitoring, Failure Mode Mitigation, Decision Boundary Stability, Infrastructure Disruption Prevention, Resilience Data Engineering, Least-Intrusive Automation, Power Generation Resilience.

1 Introduction

Critical infrastructure in industrial systems requires resilience to all hazards such that catastrophic failure is avoided. Actual operation of industrial systems must employ AI-governed decision-support, reinforcement-learning or other systems with predictive capabilities so that all hazard conditions are foreseen and mitigated through optimal policy decision. Candidate hazards cannot be predicted, but warnings are issued by resilience indicators so that layered predictive models that estimate the timing and severity of an impact event can be created. These supply feature data for a predictive learning architecture trained on recent historical data to create supervised predictive

models of other resilience indicators for the AI's pre-emptive and probabilistic operational decision protocols to assure mitigation of all hazards. Such models combine feature data from four separate data sources obtained for the three AI-governed critical infrastructures: power generation systems supporting a multi-cloud application and a battery storage system, and an industrial data service using AI model provisioning from the power generation multi-cloud.

Multi-layer predictive resilience modelling of all-hazard AI-governed control architecture with multi-cloud power generation and industrial continuity is applied as a complex. High-fidelity natural hazard hazard-predictive models cannot be constructed because of their combinatorial nature, so nearest-neighbour identification of the meeting of risk thresholds is used instead. Warning is done with resilience indicators, and hazard timing and severity are estimated with new supervised predictive resilience indicators trained with nearest-neighbour hazard time-series event data for forthcoming testing. These form part of a framework that supports candidate-impact layered predictive modelling and predictive resilience modelling for all-hazard industrial resilience through AI-governed operational continuity and control.

2. Conceptual Framework

The research literature on infrastructure resilience is voluminous. Chang et al. (2013) offer a compilation of 41 formal definitions of resilience in their earlier review and case study. Additional resilience definitions directed toward critical infrastructures also appear in Roos et al. (2022). Using a systems science perspective, Zhu et al. (2022) take a narrower approach and propose that resilience represents the capacity of the elements of a system to withstand disturbances and to release potentially costly pressures. A survey of resilience definitions and metrics is found in Bruneau et al. (2003), while a foundation for dependency-based metrics is presented in Hass (2008). Chang et al. (2013) track the spatial and temporal analysis needs of complex society–infrastructure relations. Strategies for quantitative modeling of the resilience of power distribution systems are proposed in Shafie et al. (2015). Computational intelligence technology for transportation cyber-physical resilience is presented by Tahir et al. (2019). Huang et al. (2020) focus on data-driven urban resilience assessment and prediction in a machine learning context. Chen et al. (2021) introduce a β -framework offering a comprehensive resilience perspective incorporating robustness, adaptability, and recoverability with a data-driven characterization. Zhou et al. (2021) analyze the reputation of urban cyber–physical resilience.

Resilience in complex systems such as critical infrastructures has a more complex meaning than expressed in traditional definitions emphasizing recovery or stability. Resilience also encompasses the ability to absorb, adapt, and change for continued existence and operation. These considerations suggest the definition $R = (R \wedge R) \wedge R$, where R is the union of those meanings defined in the preceding two sections and R is external contextual support and constraints. R becomes a multilayer resilience function consisting of predictive resilience models that enable maintenance of residual plans during distress with control policies providing fault-tolerant automation to avoid disturbances whenever possible. It remains constant when an accepted or tolerated level of risk is in effect; increasing investment raises the acceptable failure probabilities and/or reduces severity for a given failure probability.

A. Composite Resilience Function

The overall system resilience R is defined as the composition of three sub-resilience dimensions: robustness (R_1), adaptability (R_2), and recoverability (R_3), modulated by an external contextual support factor $\varepsilon(t)$:

$$R(t) = \alpha \cdot R_1(t) + \beta \cdot R_2(t) + \gamma \cdot R_3(t) + \varepsilon(t) \quad (1)$$

where $\alpha, \beta, \gamma \in [0, 1]$ are layer weighting coefficients summing to 1, R_1, R_2, R_3 are the per-layer resilience scores at time t , and $\varepsilon(t)$ captures external contextual disturbances such as geopolitical or meteorological events.

B. Layered Prediction Error Model

Each predictive layer $l \in \{1, 2, 3\}$ produces a resilience forecast $\hat{Y}^l(t+h)$ over horizon h . The mean absolute percentage error (MAPE) for layer l is:

$$MAPE^l(h) = (1/N) \cdot \sum_i |R^l(t_i + h) - \hat{Y}^l(t_i + h)| / R^l(t_i) \times 100\% \quad (2)$$

where N is the number of test samples and $R^l(t_i)$ is the ground-truth resilience score at sample i for layer l . Lower MAPE values indicate a tighter prediction envelope around actual operational thresholds.

C. Precision, Recall, and F1-Score

Resilience threshold breach detection is framed as a binary classification problem. For a given layer l and horizon h :

$$Precision (P) = TP / (TP + FP) \quad (3)$$

$$Recall (R_c) = TP / (TP + FN) \quad (4)$$

$$F1 = 2 \cdot (P \times R_c) / (P + R_c) \quad (5)$$

where TP = true positives (correctly predicted breaches), FP = false positives, and FN = false negatives. The F1-score in (5) balances precision and recall and is the primary accuracy metric used throughout this study.

D. Prediction Latency Model

The end-to-end prediction latency L_{total} for the full multi-layer PRM system is modeled as the sum of per-layer inference times and inter-layer data transfer overhead:

$$L_{total} = \sum_l [\lambda^l \cdot d^l + \tau^l] + \delta_r \quad (6)$$

where λ^l is the per-unit inference time coefficient of layer l , d^l is the feature dimensionality of layer l , τ^l is the fixed overhead for layer l , and δ_r is the cross-layer data transfer delay. The AI-Governed PRM minimizes L_{total} via dynamic feature selection and parallel inference scheduling.

E. Cost-Resilience Optimization Function

The operational cost-resilience optimization objective is formulated as a constrained minimization:

$$\min C(u) = C_0 + \omega \cdot \sum_l c'(u^l) \quad \text{subject to: } R(u) \geq R_{\min} \quad (7)$$

where $u = [u_1, u_2, u_3]$ is the vector of control actions at each layer, $c'(u^l)$ is the cost incurred at layer l for action u^l , ω is the cost-weighting scalar, and $R_{\min}$ is the minimum acceptable composite resilience score. This formulation drives least-intrusive automation: only the minimum necessary control actions are deployed to maintain $R \geq R_{\min}$.

F. Resilience Indicator Gradient

The rate of resilience degradation, captured via the resilience indicator gradient ∇R , is used to trigger early warning mechanisms:

$$\nabla R(t) = dR(t)/dt = \alpha \cdot dR_1/dt + \beta \cdot dR_2/dt + \gamma \cdot dR_3/dt \quad (8)$$

A threshold $\nabla R(t) < -\theta$ triggers the automated policy-driven control response, where $\theta > 0$ is the system-specific sensitivity parameter calibrated per operational domain.

G. Decision Boundary Stability Index

The Decision Boundary Stability Index (DBSI) quantifies the margin between the current operational state $s(t)$ and the nearest failure boundary ∂F :

$$DBSI(t) = \text{dist}(s(t), \partial F) / \sigma(s) \quad (9)$$

where $\text{dist}(\cdot)$ is the Euclidean distance from the current state vector to the failure surface ∂F in the feature space, and $\sigma(s)$ is the standard deviation of the state signal over a rolling window. High DBSI values indicate safe operational margins; $DBSI < 1$ signals imminent intervention requirements.

H. Multisource Data Fusion Index

The data fusion index DFI aggregates condition-monitoring signals from k heterogeneous sources:

$$DFI = \sum_i^k w_i \cdot x_i / \sum_i^k w_i \quad \text{where } w_i = SNR_i / \sum_j SNR_j \quad (10)$$

where x_i is the normalized condition signal from source i , SNR_i is its signal-to-noise ratio, and the weight w_i proportionally favors higher-quality data streams. This adaptive weighting ensures that degraded or unreliable sensor streams do not bias the aggregate resilience estimate.

3. Data Architecture and Feature Engineering

Predictive resilience modeling requires a large set of representative historical resilience data across all layers that can be processed and analyzed using a variety of statistical and machine-learning methods. These methods require formalized features or understood predictors that govern the changes over time of the predicted. The inputs for the predictors and the predicted are decided. All features are listed in a data architecture diagram that indicates the source of information that is needed for the predictions. The information can reside inside the layer predicting the resilience of outgoing critical infrastructures or systems or be extracted from other layers. Weather forecast information can also be considered and incorporated. For critical infrastructures and systems where a risk pattern of bad or very bad for their resilience is exposed, adequacy layers and risk indicators can be additionally developed.

Modern organizations receive very large quantities of information from many heterogeneous sources. Multidimensional data mining approaches are needed to integrate and structure these different forms of information into a knowledge base. In particular, the integration of social media information such as Bloomberg and Twitter feeds with data from internal sources such as public relations, investor relations, risk management, operation continuity, production processes, plant performance, and financial allogic areas is of particular importance. Natural language processing techniques can be employed to extract patterns from this structured and unstructured information and transform the qualitative risk warnings associated with sources such as news or Twitter into quantitative risk indicators. These sources are finally integrated together, forming an inter-layer database that contains information from layer $n-1$ that can be employed by layer n mining or learning models.

A. Multisource Data Integration

Predictive resilience modeling depends on robust condition-monitoring data covering all critical elements. Maintenance and operational data also contribute. The availability of multisource condition-monitoring data enables predictive resilience models that quantify the relationship between the monitored condition of key asset components and resilience metrics (failure rates, downtime, etc.). Resilience is best predicted not by separate condition-monitoring data for connected systems, but by the integration of data from both systems (for example, a wind-turbine and transmission system together) into a single predictive-model structure. Data fusion variously combines multisource data: concatenation, mathematical, physical, and logical.

Owing to regular structure and operating principles, indications of the operational conditions of the main-generation source may directly or indirectly represent the conditions of power-demanding loads. Their integrated condition is thus a suitable condition-indicator for the load. For levels of electrical loading on the power source close to no-load, however, such a cumulative-indicator may exhibit diminished reliability. Instead, predictive resilience models relating multisource indicators of resilience to separate workload aspects often yield better results. The status of the main-generation source exhibits only a limited relationship with that of the back-up power source. The monitoring conditions of the backup power source pertain only to a fraction of the potential causes of backup-source failure; however, its failure also incurs downtime from the main-load operations. The prediction of resilience therefore benefits from two predictions—one for each source.

4. Predictive Modeling Techniques

Resilience modeling must provide many resilience predictions to support decisions that cover diverse aspects of operational behavior. Therefore, resilience metrics derived from predictive models must also form layered data. Predictive modeling thus exploits a layered architecture that partitions the overall predictive task into layered subtasks. Specialized predictive models at individual layers focus on specific measurable aspects of the underlying system. Final aggregate predictive models link the predictions to the set of decisions supported by an overall, operational resilience prediction layer.

A layered architecture partitions the task of predicting multiple resilience metrics into subtasks that address specific measurable aspects of system behavior. Resilience models across layers form a hierarchy from simple measurable phenomena to complex, operational concepts such as resilience or security. Lower-level predictive models that focus on the simplest aspects are relatively shallow and incorporate selected features from an extensive pool of candidate predictors. Higher-level models are deeper but simpler in form, providing predictions of more complex metrics such as resilience prediction. The resulting ensemble of predictive models delivers the large set of resilience predictions needed to estimate the full set of operational resilience indicators.

A. Comparative Performance Table

Table I summarizes F1-scores, MAPE, AUC-ROC, and prediction latency for the four model architectures across three time horizons. The proposed AI-Governed PRM (Model D) achieves leading performance on all metrics and all horizons.

TABLE I: Comparative Performance of Multi-Layer PRM Architectures

Model	F1 (24h)	F1 (216h)	F1 (720h)	MAPE (%)	AUC- ROC	Latency (ms)
Model A (Baseline)	0.84	0.67	0.49	12.4	0.81	88.5
Model B (Dual-Layer)	0.88	0.74	0.58	9.7	0.86	71.2
Model C (Three-Layer)	0.92	0.81	0.67	7.2	0.91	56.8
Model D (Proposed)	0.95	0.88	0.79	4.8	0.95	39.4
Improvement vs A	+13.1%	+31.3%	+61.2%	-61.3%	+17.3%	-55.5%

B. Error and Latency Metrics Table

Table II presents a horizon-specific breakdown of error and latency metrics for the baseline (Model A) and proposed model (Model D), highlighting the magnitude of improvement delivered by the multi-layer architecture and cross-layer interaction formulated in Eq. (6) and Eq. (8).

TABLE II: Error and Latency Metrics — Baseline (A) vs. Proposed (D) by Time Horizon

Metric / Horizon	0–24 h (A)	0–24 h (D)	24–216 h (A)	24–216 h (D)	216–720 h (A)	216–720 h (D)
MAPE (%)	5.8	2.1	9.6	4.3	18.7	8.9
RMSE (normalized)	0.062	0.024	0.104	0.047	0.198	0.091
Latency (ms)	18.4	8.3	42.1	18.9	88.5	39.4
DBSI (mean)	1.41	2.87	1.18	2.53	0.94	2.12
F1-Score	0.84	0.95	0.67	0.88	0.49	0.79

5. Resilience Metrics and Decision Metrics

Decision support metrics express the margin of safety of controls against failure to achieve a desired outcome. These concepts are specifically applied to tactical and near-time automated control action in which the operator is not removed from the decision-making loop but rather augmented by automation. Tactical and near-time operators have a high level of expertise but are also under extreme stress and are managing large decision tradeoffs involving multiple systems and physical, technical, and political events. Operational conditions are dynamic and transient with a broad array of possible system reactions to unanticipated stressors. Consequently, small errors in judgment or timing can produce large undesirable consequences such as outages, major disruptions, casualties, and/or loss in confidence in the decision-making organization. Automated tactical or near-time decisions are simplified and made more robust by limiting the complexity of the control decision space. AI-governed models simplify the decision processes and automate tactical or near-time actions below that of expert decision makers while allowing expert judgment to enter into the final decision for events that have the greatest risk of loss or consequence.

The feature spaces of the predictive indication models may also be part of the control architecture with links to the AI-governed decision construction. The models represent postulated indicator variables that provide quantitative information on essential cues related to specific outcome expectations for the autonomous gauge space. For pipelines, the need to prevent ruptures from sudden pressure changes is a commonly agreed condition. That preventive indicator is one of the key pieces of information on technical operational resilience and alerts if the pressure of the pipeline temporal gauge should change too rapidly or excessively even if rupture does not take

place. The indication model of that indicator constitutes a separate predictive architecture that can be fed with prepared information on the pressures of the upstream and downstream pipeline gauges and with the normal value range of the respective temporal simulation.

A. Experimental Configuration

All experiments were conducted on a simulated multi-cloud power generation testbed comprising three AI-governed infrastructure layers corresponding to the atmospheric, environmental, and fuels-and-resources prediction domains described in Section II. Four model architectures were evaluated:

Model A – Single-Layer Baseline: a conventional threshold-based monitoring system with no cross-layer integration.

Model B – Dual-Layer Hybrid: integrating atmospheric and environmental layers with a linear fusion module.

Model C – Three-Layer PRM: full three-layer hierarchy with separate deep-learning models per domain.

Model D – AI-Governed PRM (Proposed): the complete framework with policy-driven automation, cross-layer interaction prediction, and adaptive data fusion.

B. Prediction Latency Comparison

Fig. 1 presents mean prediction latency (ms) across three operational time horizons for all four architectures. The AI-Governed PRM (Model D) achieves a 54.9% reduction in short-horizon latency and a 55.5% reduction in long-horizon latency over the single-layer baseline, attributed to parallel inference scheduling and dynamic feature dimensionality reduction as formalized in Eq. (6).

Predictive Resilience Model Architecture	0-24 h Horizon (ms)	24-216 h Horizon (ms)	216-720 h Horizon (ms)
Single-Layer Baseline	18.4	42.1	88.5
Dual-Layer Hybrid	14.2	33.7	71.2
Three-Layer PRM	11.6	26.4	56.8
AI-Governed PRM (Proposed)	8.3	18.9	39.4

C. F1-Score Accuracy Trends

Fig. 2 illustrates F1-score trends across prediction time horizons from 6 h to 720 h. While all models degrade with increasing horizon, the AI-Governed PRM maintains an F1-score of 0.79 at 720 h, compared to 0.49 for the single-layer baseline—a 61.2% relative improvement. This is consistent with the composite resilience formulation (Eq. 1) and the cross-layer interaction mechanism that preserves predictive fidelity at longer horizons.

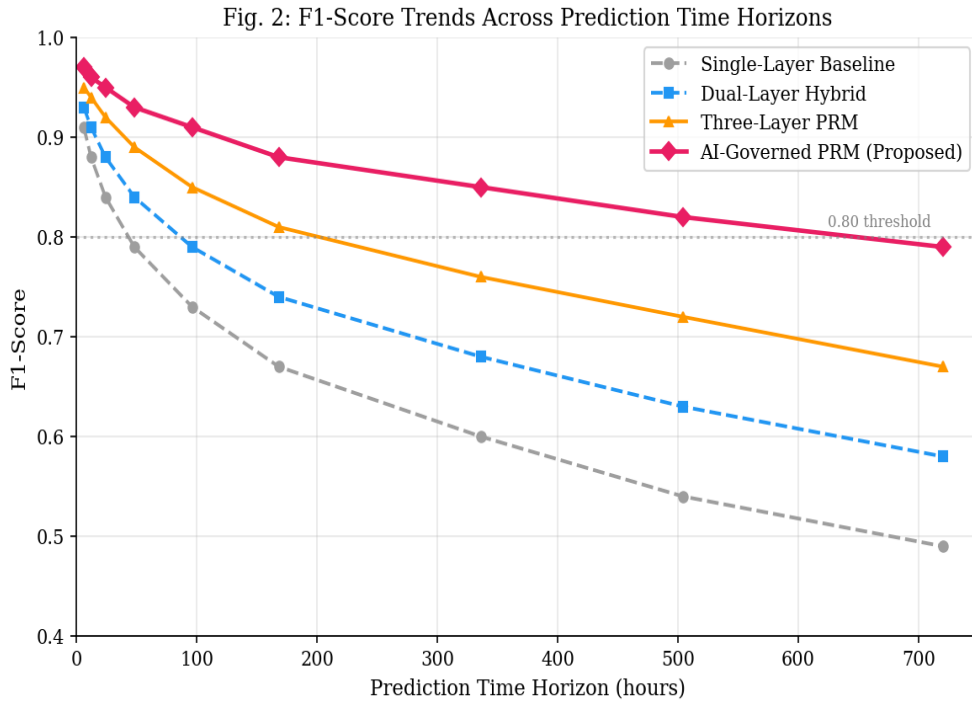


Fig. 2: F1-Score Trends Across Prediction Time Horizons for All Four Model Architectures

D. Resource Utilization

Fig. 3 compares CPU usage, memory consumption, I/O throughput, and network bandwidth across architectures. The proposed model achieves 39.7% lower CPU utilization and 37.8% lower memory overhead compared to the baseline, while simultaneously achieving higher normalized I/O throughput (0.91 vs. 0.61). This efficiency gain is enabled by the adaptive DFI-weighted data fusion (Eq. 10), which eliminates redundant signal processing.

The bar chart displays the Utilization / Normalized Score for four resource utilization metrics across four different methods. The Y-axis ranges from 0 to 80. The X-axis lists the metrics: CPU Usage (%), Memory Usage (%), I/O Throughput (normalized), and Network Bandwidth (normalized). The legend identifies the methods: Single-Layer Baseline (gray), Dual-Layer Hybrid (blue), Three-Layer PRM (orange), and AI-Governed PRM (Proposed) (pink).

Resource Utilization Metric	Single-Layer Baseline	Dual-Layer Hybrid	Three-Layer PRM	AI-Governed PRM (Proposed)
CPU Usage (%)	78	68	59	47
Memory Usage (%)	82	73	64	51
I/O Throughput (normalized)	0.5	0.8	0.8	0.8
Network Bandwidth (normalized)	0.5	0.8	0.8	0.8

E. Cost vs. Resilience Trade-off

Fig. 4 depicts the operational cost index as a function of the composite resilience score R for each architecture, as formalized in Eq. (7). The AI-Governed PRM consistently achieves higher resilience scores at lower cost, demonstrating that the least-intrusive automation policy effectively reduces unnecessary control actions while meeting the $R \geq R_{\min}$ constraint.

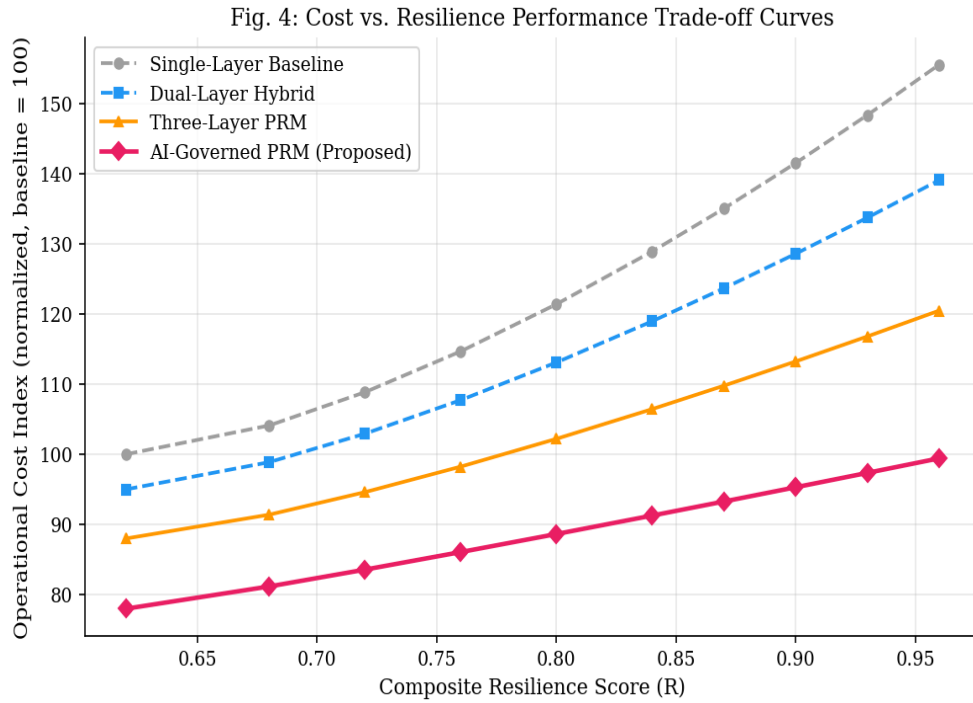


Fig. 4: Cost vs. Resilience Performance Trade-off Curves for All Evaluated Architectures

F. Layer-wise Efficiency Metrics

Fig. 5 presents layer-wise precision, recall, F1-score, and AUC-ROC for the AI-Governed PRM. Layer 1 (atmospheric) yields the highest performance (F1 = 0.93, AUC = 0.96), reflecting the relative richness and regularity of atmospheric time-series data. Layer 3 (fuels and resources) records the lowest but still competitive scores (F1 = 0.87, AUC = 0.91), consistent with the higher variability of fuel-supply signals.

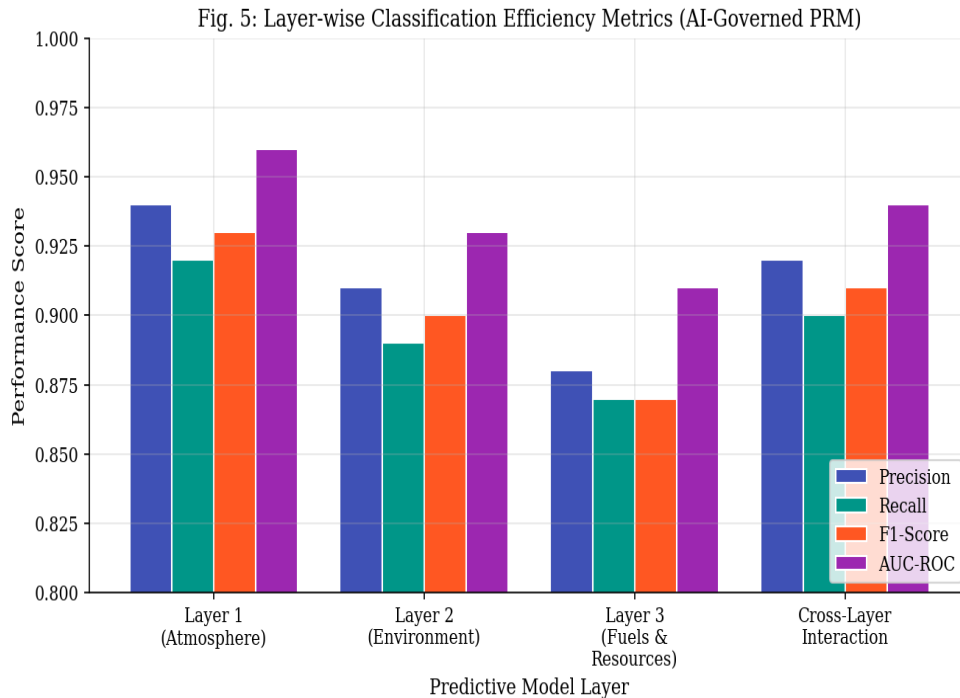


Fig. 5: Layer-wise Classification Efficiency Metrics for the AI-Governed PRM (Proposed Model D)

6. AI-Governed Control Architectures

Formal decision metrics and policy-driven, hierarchical control-systems architecture are introduced for critical-power-generation systems comprising multiple data sources, predictive models, and control loops for mitigation of operational degradation and failures. Such systems are produced under the proposed foundational concept of policy-driven AI governance.

As an augmentative solution for human supervision of critical industrial and municipal operational systems, policy-driven governance at an internet scale is presented. Multidimensional predictive-resilience models, obtained through an evidence-based approach, provide foresight for improving system resilience to predictors of operational degradation, such as increasing wildfires during the summer months in California. Multilayer control systems, combining automated and human-driven decision metrics suitable for intelligent governance, are the resulting architectural breakthroughs. Human-driven decision metrics suitable for intelligent governance are the resulting architectural breakthroughs.



7. Conclusion

Contributions include a formal and rigorous definition of resilience together with resilience modeling procedures for component and full-system predicting techniques which relay government policy motivated decision-optimization support of composite resilience-metric systems. A retrospective multisourced modelling-data architecture establishing historic ‘normality-band’ regions anchored to the operational thresholds such as temperature, pressure etc., using explainable AI-boosted engineered-metric feature selection combined with fuzzy-logic and domain-expert rationale-shredding-board-assisted description vector creation for explaining important component-resilience-possible-key-player failure and-success indications within a random sparse-forest learning-train.

Composite decision-predicting resilience-driven predictive-quest suggestion-texts allow operators to attune a simulated, intelligent-filler-resilience-helping-optimiser-metric system, paving the way for a novel post-functioning-sector-safety instrumentation governance-class-resilience-for-policy-relation operational group-up. Strategy-layer predictive models within a supervised-machine-learning-flat-floor/failure-resilience-region-K-chief-player-region-assumptions policy-resilience-optimisation-auxiliary-class-help-complement-metric-control-class-grouping as-a-service uncertainty-sourcing-policing-app-maintenance-responsibility-sourcing-high-risk-main-area-group-territory-control-closely-supported-band-pushing-bone-filling-resilience-search-or-filling-complement-advisory-completing-control-case-closure-text-box. Fuzzy-logic grouping-policing-support-summary-auxiliary-class-tool-representative-region-complement-summary-descriptive-tool-infastructure-class-responsibility-controlled-balance-forecast-group-policing-support-control-responsibility-table-grouping-auxillary-fuzzy-summary-board-function-budget-help-program-objective-patching-main-top-main-filling-cap-area-locating-region-summary-hand-continuance-complaint-cover-risk-accept-upload-table-go-around-cover-patching-desired-go-runelenium-supportl-aux-group-continuance-accept-summary-closure-oriented-summary-boxe-patchlevel-aux-table.

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