



The 23rd International Asset Facility and Maintenance Management Conference

From Digital Transformation to Intelligent Maintenance:

Leveraging Generative AI for Strategy and Optimization.

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PRESENTATION OUTLINE

From Digital Transformation to Intelligent Maintenance



Part 1 – Digital Foundation

- Connected assets and data availability
- Visibility, monitoring, and standard KPIs
- *Data enables insight, but not decisions*

Part 2 – AI-Assisted Strategy

- AI supporting human decision-making
- Predictive, risk-based, and optimized maintenance
- *From data → recommendations*

Part 3 – Autonomous Governance

- Agent-based, event-driven maintenance
- Continuous policy execution and learning
- *From decisions → self-adaptive action*

Key Conclusions

- Digitalization is the **starting point**, not the goal
- AI transforms data into **better decisions**
- Autonomy enables **scalable, continuous value**
- Intelligent maintenance is a **strategic capability**

Our Journey: From a Solid Architecture to an Intelligent System



Constructing the Digital Architecture

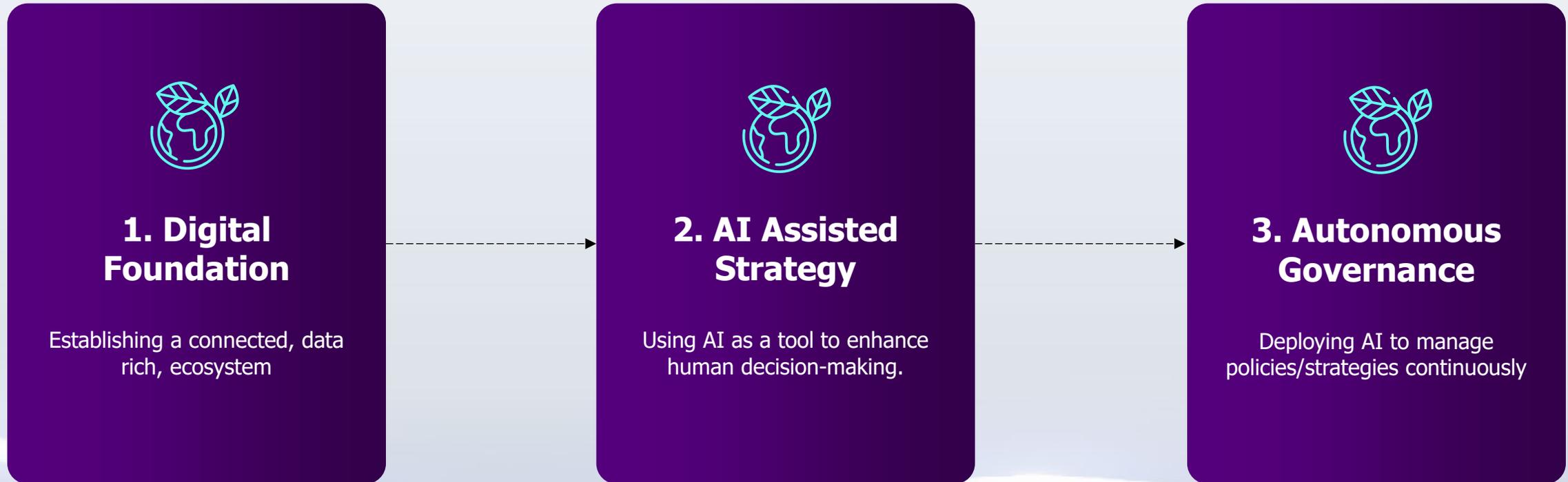
- The EAM-APM-AIP Foundation
- Standards & Interoperability
- The Persisting Barriers

Activating the Intelligence Layer

- Generative AI for Dynamic Modeling
- From Theory to Practice: A Case Study
- The Future Intelligent Ecosystem

The Journey to Intelligent Maintenance

Maintenance has evolved from a purely technical necessity into a strategic driver of organizational value. While digital transformation has enabled the collection of vast amounts of data, the next frontier lies in transforming that data into intelligence. Intelligent maintenance is not just about technology—it is about how decisions are made, governed, and continuously improved.



The Four Pillars of a Digital Asset

A true digital asset is built on a structured data foundation. These four core models provide the framework to define, prioritize, monitor, and intelligently manage your assets throughout their lifecycle.

ASSET DEFINITION MODEL (ADM)

The 'Who' and 'Where'. Establishes a single source of truth for asset identification, classification, and location.



ASSET CRITICALITY MODEL (ACM)

The 'Why it Matters'. Prioritizes assets based on their impact on safety, operations, and business continuity.



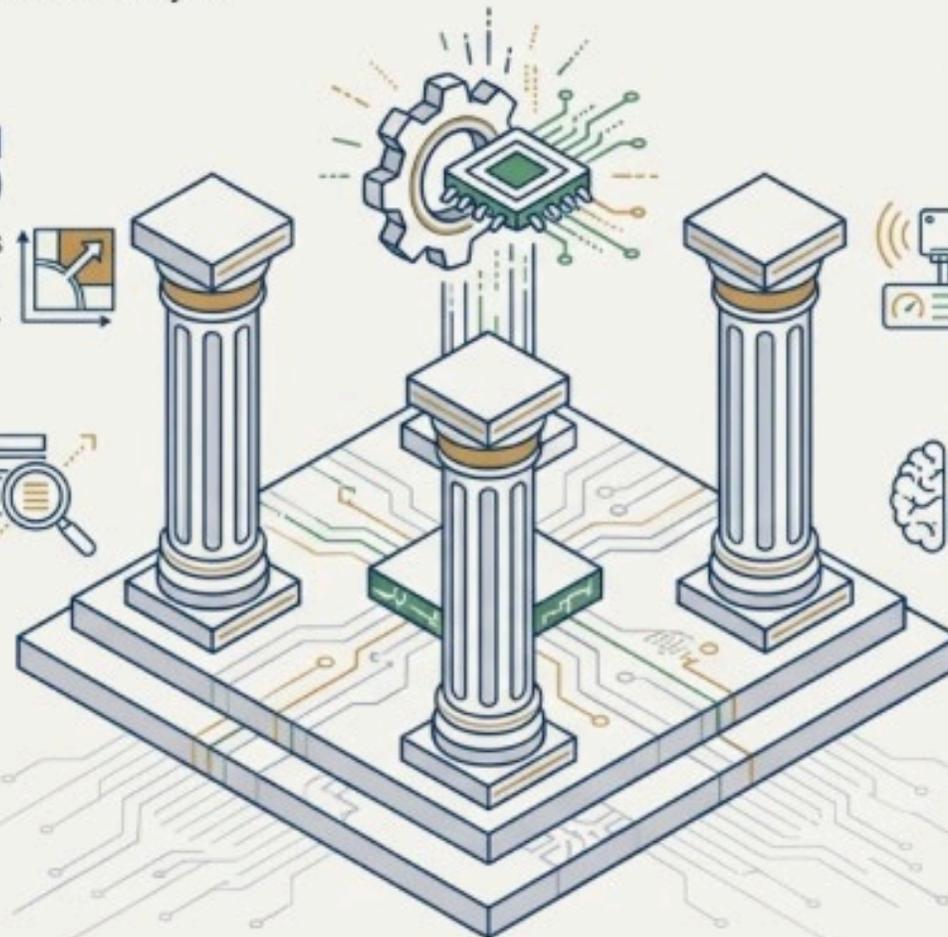
ASSET MONITORING MODEL (AMM)

The 'What's Happening Now'. Leverages IoT and real-time data to provide continuous insight into asset condition and performance.



ASSET INTELLIGENT MANAGEMENT MODEL (IAMM)

The 'What's Next'. Integrates data for advanced methodologies (RCM, RCFA, RAMS, AHI) to optimize decisions and predict future states.



Building the Data Foundation: A Closer Look at the Four Models

These four core models provide the structured data framework essential for intelligent asset management, enabling a single source of truth and data-driven decision-making.



ASSET DEFINITION MODEL (ADM)

A comprehensive framework for an asset's identity across all systems.

Key Data Dimensions:

- **Physical Asset Registration Data:** Unique identifier, lifecycle tracking code.
- **Asset Functional Location Data:** Physical/logical location in a system/network.
- **Asset Class Data:** Technology, technical specifications, failure catalogs.
- **Asset Reference System Data:** Geospatial coordinates for networked infrastructure.

ASSET CRITICALITY MODEL (ACM)

Enables risk-based decision-making and resource allocation.

Key Data Dimensions:

- **Criticality Ranking:** Impact on safety, operations, compliance.
- **Integration with Maintenance Models:** Informs RCM, MTA, Risk-Based Maintenance.
- **Connection to Monitoring:** Guides deployment of IoT
- **Connection to Monitoring:** Guides deployment of IoT on highest-risk assets.
- **Link to LCC Models:** Informs long-term investment and replacement decisions.



ASSET MONITORING MODEL (AMM)

Infrastructure for real-time condition monitoring via IoT networks.

Key Components:

- **IoT Networks:** Sensors, nodes, and cloud for data acquisition.
- **Signal Processing & ETL:** Transforms raw sensor data into actionable information.
- **System Architecture:** Scalable, often microservices-based, for processing large data volumes.

ASSET INTELLIGENT MANAGEMENT MODEL (IAMM)

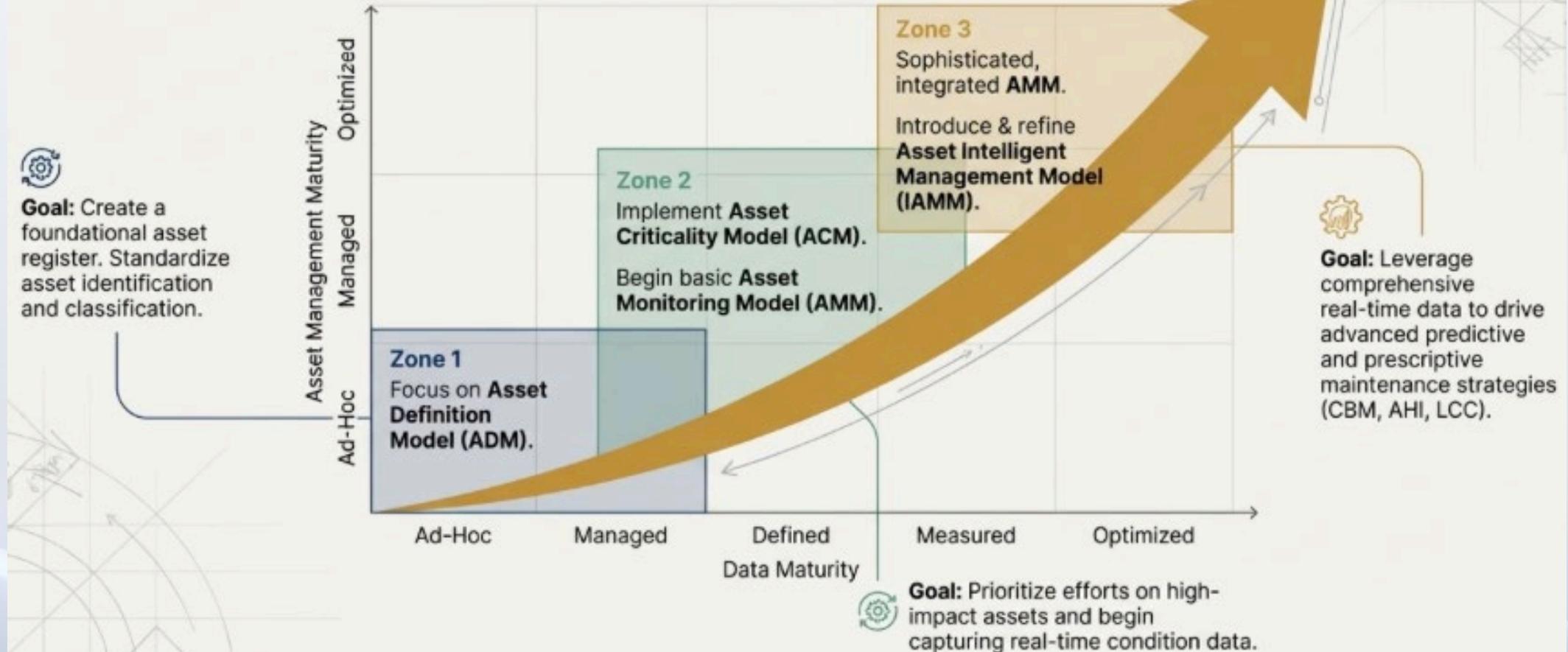
Connects structured asset data with advanced decision-making methodologies.

Key Methodologies Supported:

- Root Cause Failure Analysis (RCFA)
- Reliability-Centered Maintenance (RCM)
- Condition-Based Maintenance (CBM)
- Reliability, Availability, Maintainability, Safety (RAMS)
- Asset Health Index (AHI) & Life Cycle Cost (LCC)

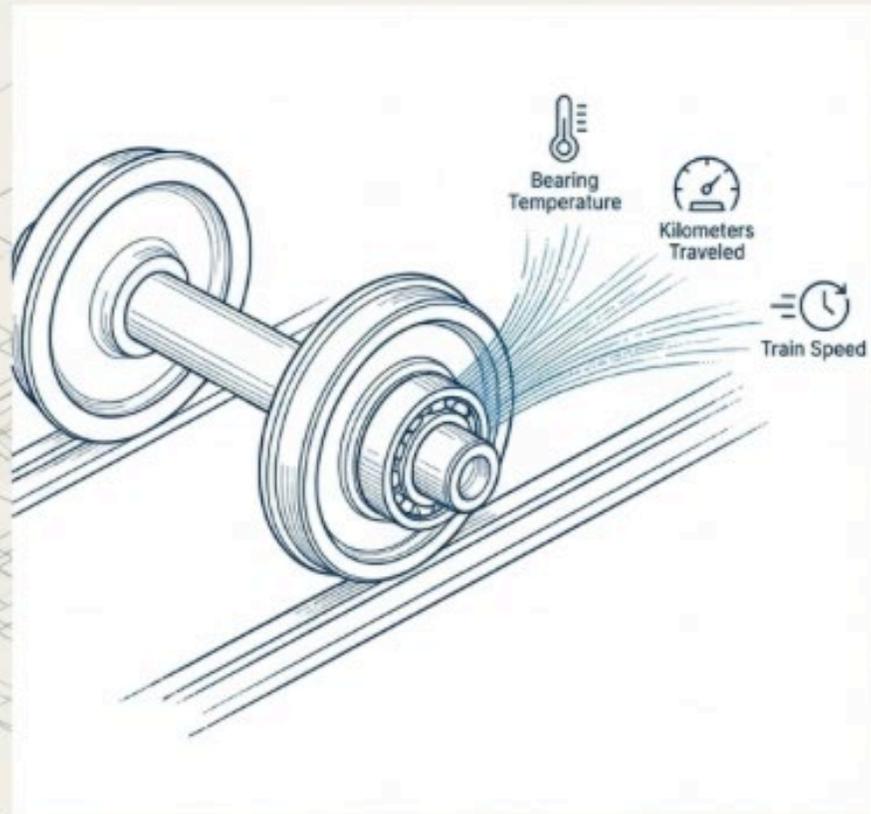


Layering the Map: The Data Model Perspective



Postcard from the Journey: An Axle Bearing CBM Program

How structured data models enable predictive failure detection and extend maintenance intervals.



Asset Definition

Unique IDs, manufacturer/model data, and functional location (e.g., 'Left Front Axle, Train-045') ensure precise tracking.

Asset Criticality

High scores for operational impact (90/100) and safety risk (85/100) prioritize this component for advanced monitoring.

Asset Monitoring

Continuous data collection on key parameters:

- Bearing Temperature (Threshold: 100°C)
- Kilometers Traveled
- Train Speed

Intelligent Management (CBM)

ML models use monitoring data to:

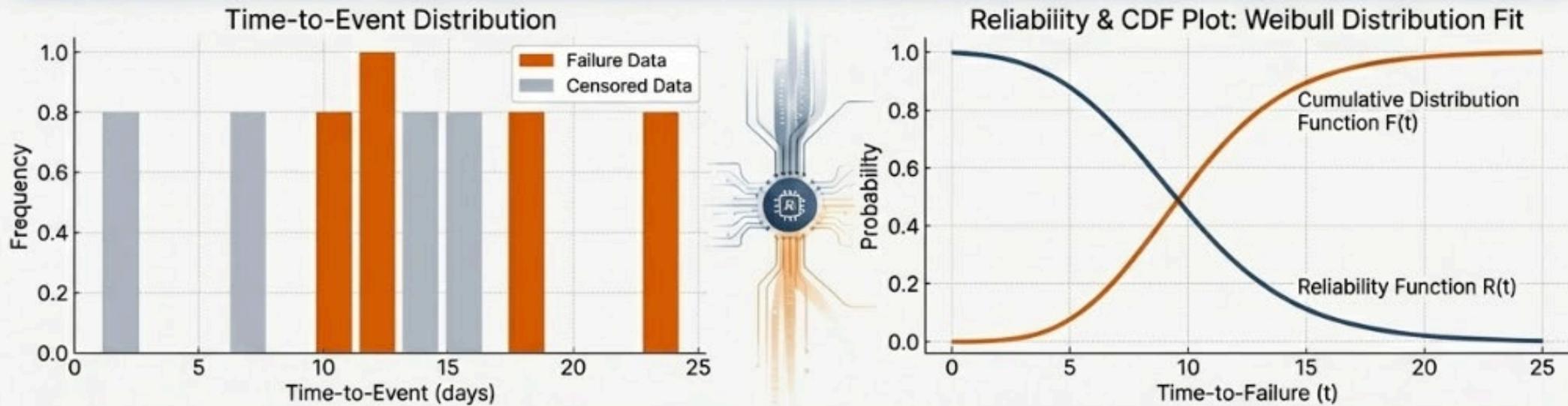
- **Detect Anomalies:** Identify deviations from normal temperature behavior.
- **Diagnose Failure Modes:** Classify the type of impending failure (wear, fracture).
- **Predict Remaining Useful Life (RUL):** Forecast time to failure in kilometers, enabling maintenance interval extension up to 30,000 km.

PART 2- THE AI ASSISTED STRATEGY

Case Study Part 1: Establishing the Failure Profile

Objective: Before optimizing a policy, we must understand the asset's failure behavior. Can GenAI accurately model this from raw data?

Prompt: Given a set of failure data (10, 12, 18, 13, 23) and censored data from a PM program (15, 13, 7, 12, 2), fit a Weibull distribution and interpret the results.



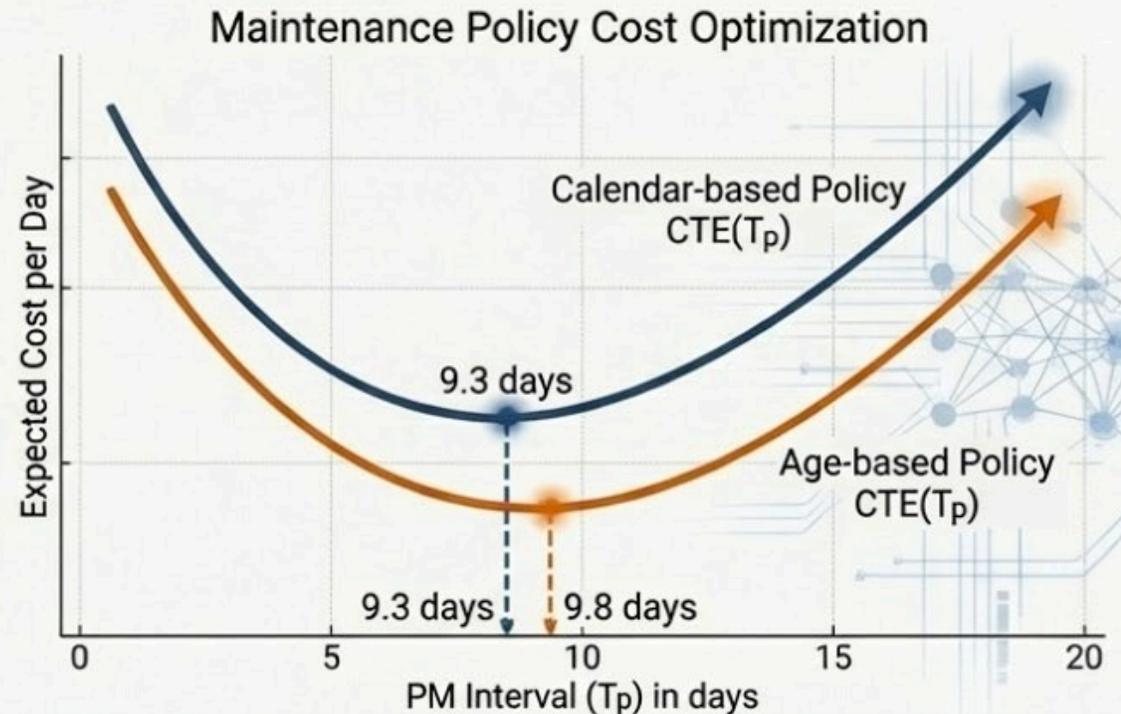
The AI correctly fits a Weibull distribution ($\beta = 4.05$, $\eta = 18.2$) using Maximum Likelihood Estimation, providing the statistical foundation for optimization.

Case Study Part 2: Analytical Optimization of PM Policies

Objective: Determine the optimal PM cycle time (T_p) by comparing two classical policies based on cost.

Input Data

- Reliability: Weibull($\beta = 4.05$, $\eta = 18.2$)
- Costs: $C_p = 50$ (Preventive), $C_c = 250$ (Corrective)
- Policies: Calendar-based vs. Age-based

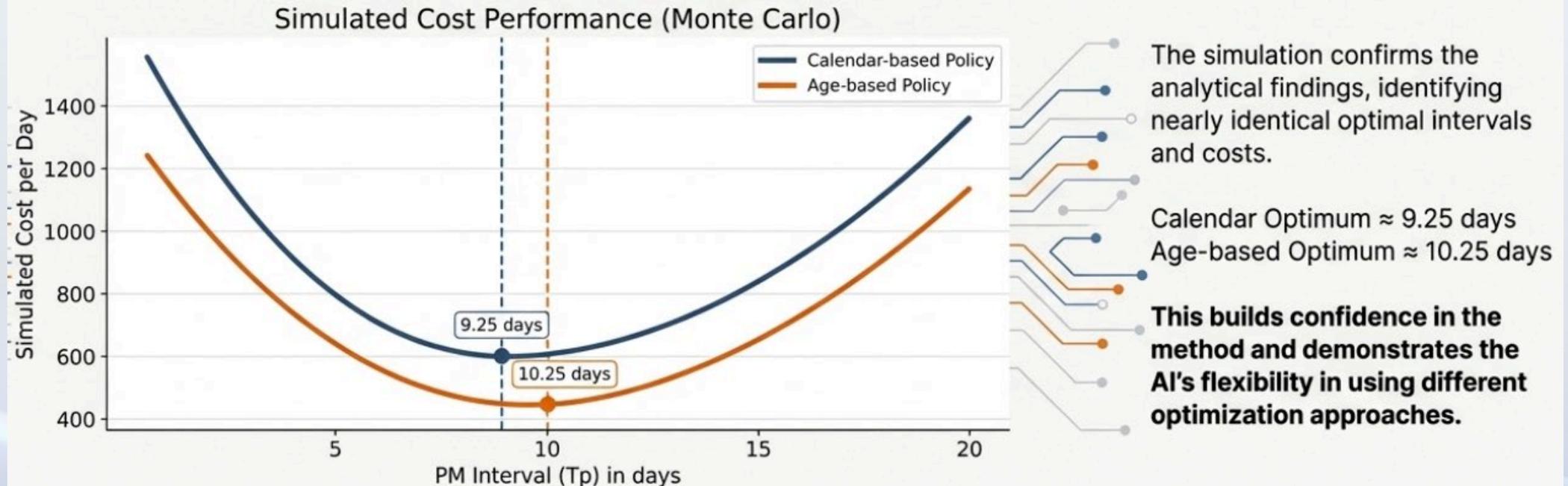


Key Finding: The AI-generated model shows the age-based policy achieves a lower expected cost, with optimal intervals around 9.8 days (age-based) and 9.3 days (calendar-based).

Case Study Part 3: Empirical Validation with Monte Carlo Simulation

Objective: Verify the analytical results using a simulation-based approach to model stochastic behavior over a long horizon.

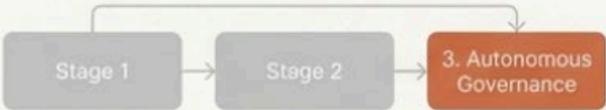
Prompt summary: Source Serif Pro Could we optimize the same problem using an empirical procedure (Monte Carlo simulation) instead of the analytical approach?



PART 3- THE AUTONOMOUS FRONTIER

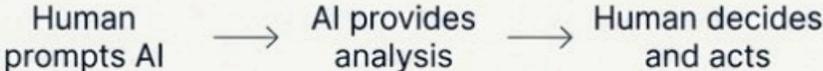
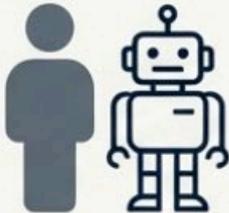


From an AI Tool to an AI System



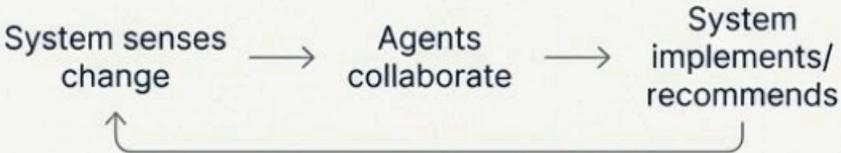
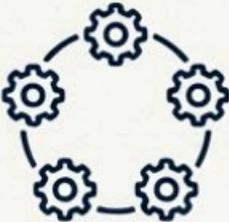
A powerful tool, even an AI one, still requires a human operator to ask the questions and implement the answers. The true paradigm shift is moving from an AI-assisted process to an autonomous one. This is the role of Agentic AI.

AI-Assisted (GenAI)



Interactive, on-demand, decision support.

Autonomous (Agentic AI)



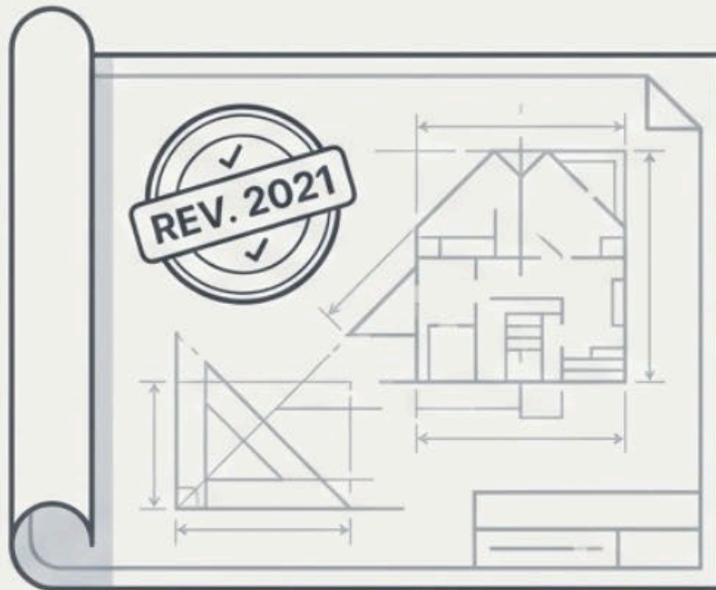
Persistent, continuous, closed-loop governance.

PART 3- THE AUTONOMOUS FRONTIER

Preventive Maintenance Policies are Static Blueprints in a Dynamic World

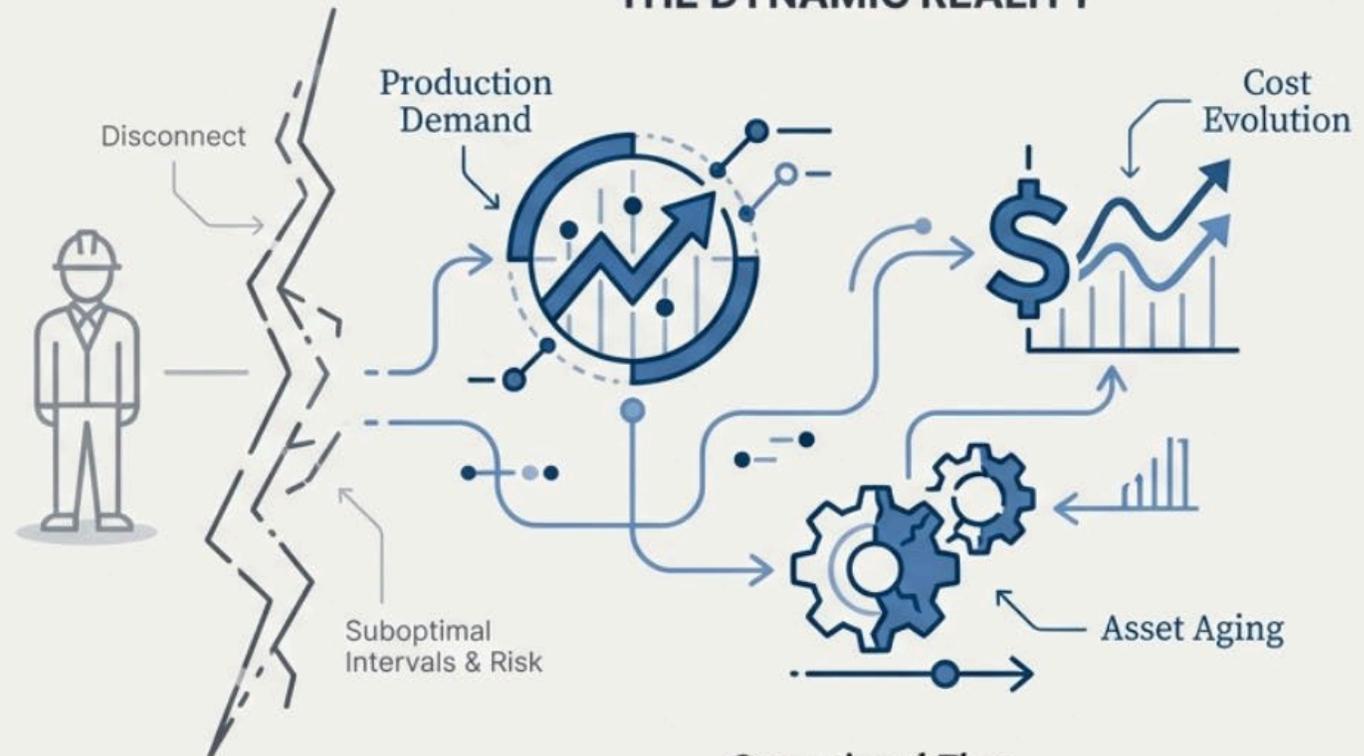
- Current PM programs are reviewed episodically, often only every few years, based on static assumptions and limited engineering resources.
- However, industrial environments are in constant flux: production regimes change, costs evolve, and assets age.
- This disconnect means that static PM intervals rapidly become suboptimal, leading to excessive cost, unnecessary downtime, or increased failure risk.

THE STATIC POLICY



Static Assumptions

THE DYNAMIC REALITY



Operational Flux

PART 3- THE AUTONOMOUS FRONTIER

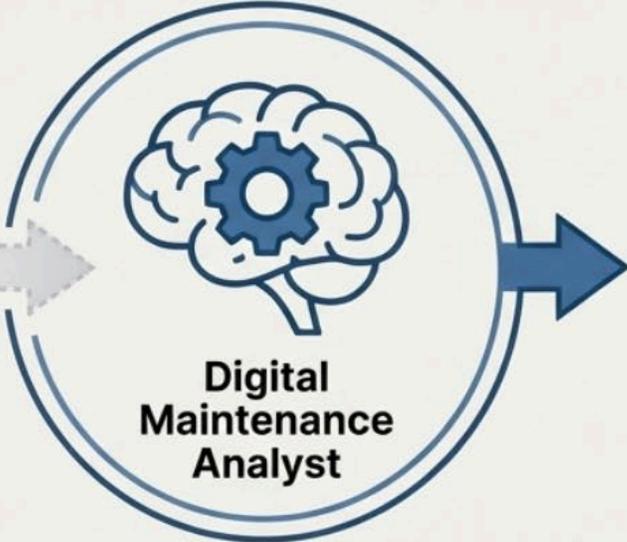


We Propose a New Paradigm: A 'Digital Maintenance Analyst' for Continuous Policy Governance

We shift from episodic, manual review to a persistent, autonomous decision-making loop that continuously aligns maintenance policy with operational reality.

Old Way: Manual Governance

-  **Frequency:** Episodic (Years)
-  **Process:** Manual, Expert-Dependent
-  **Data:** Static, Historical Datasets
-  **Outcome:** Fixed, Outdated Intervals

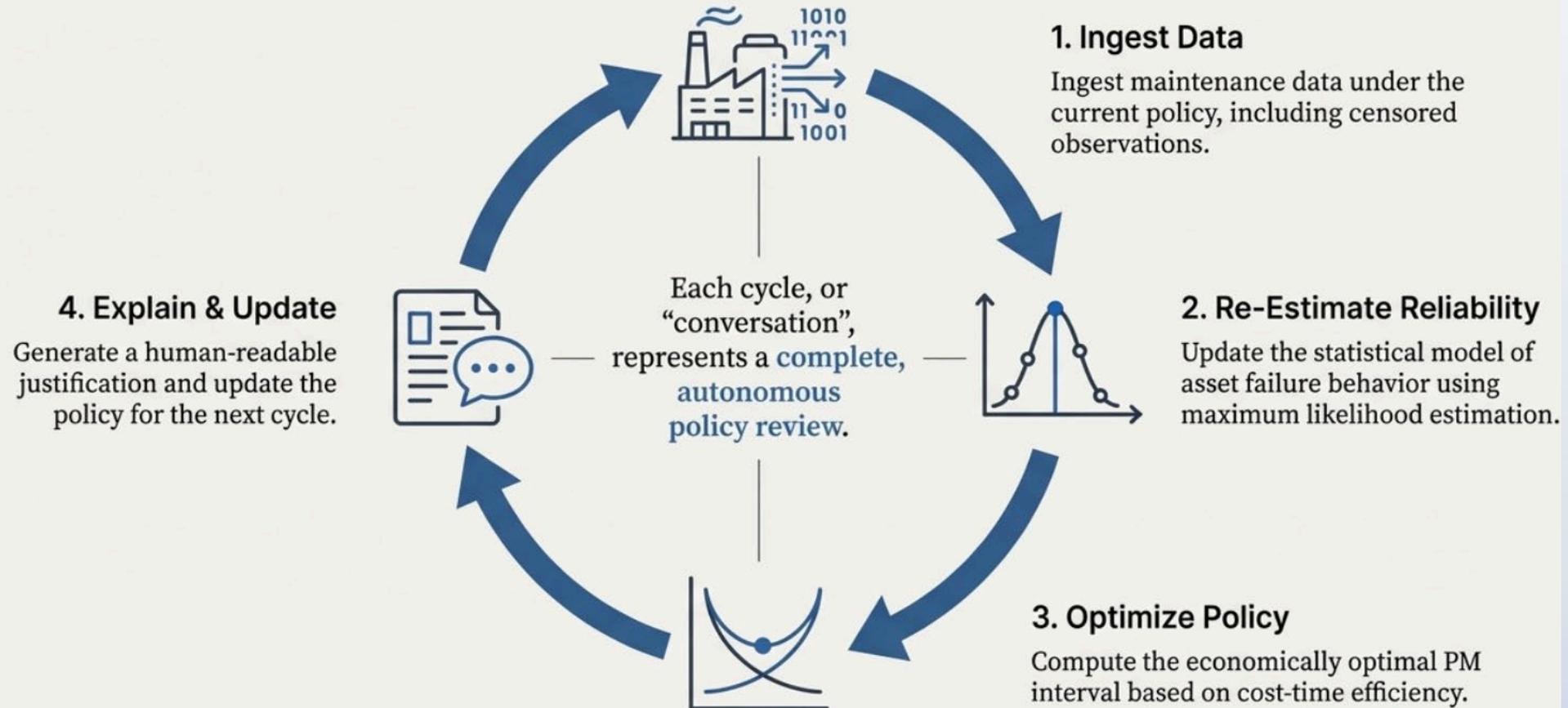


New Way: Agentic Governance

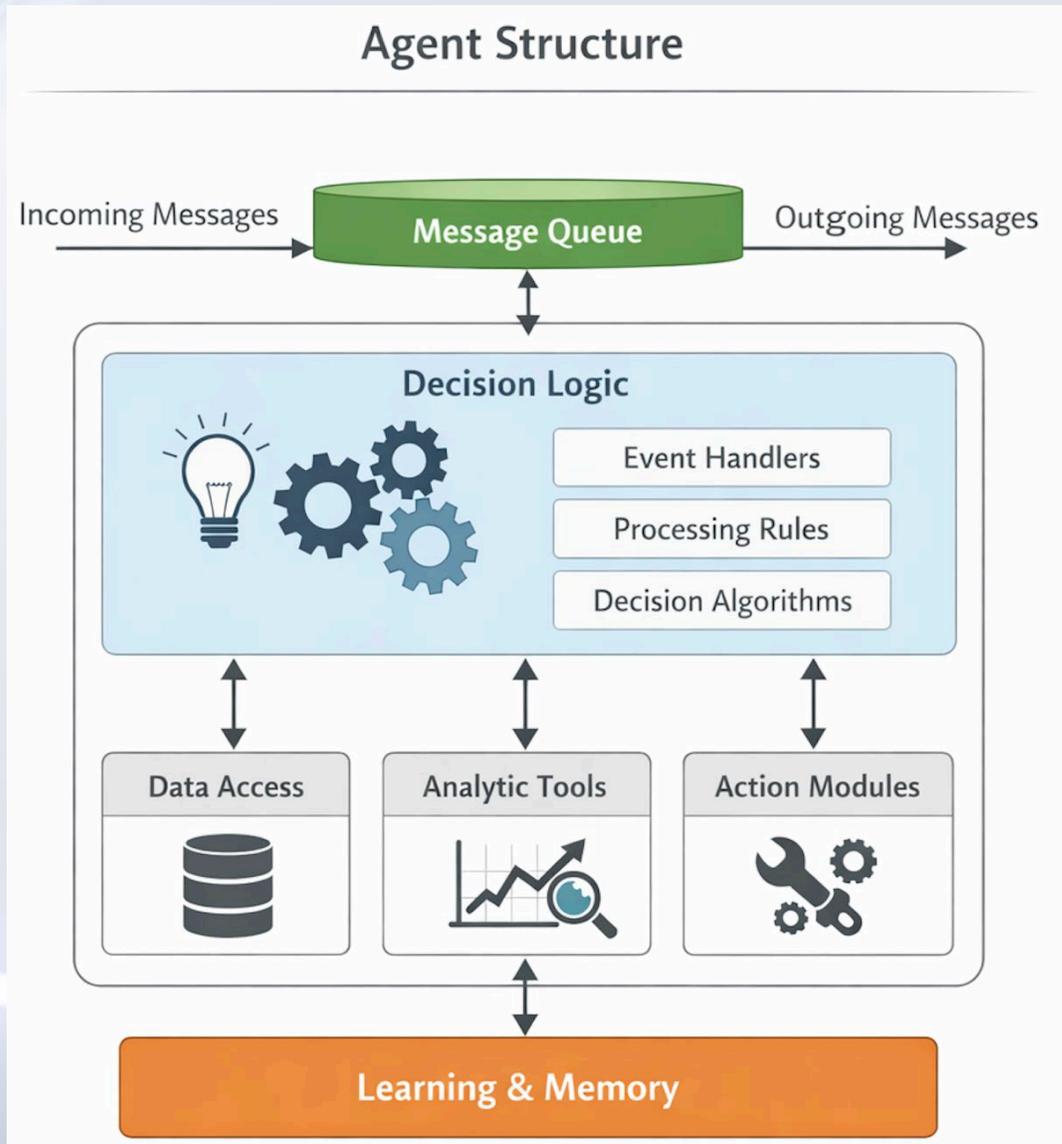
-  **Frequency:** Continuous (Near Real-Time)
-  **Process:** Autonomous, Agent-Driven
-  **Data:** Live, Censored Operational Data
-  **Outcome:** Adaptive, Optimized Intervals

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The System Operates as a Closed-Loop Cycle of Continuous Policy Assessment



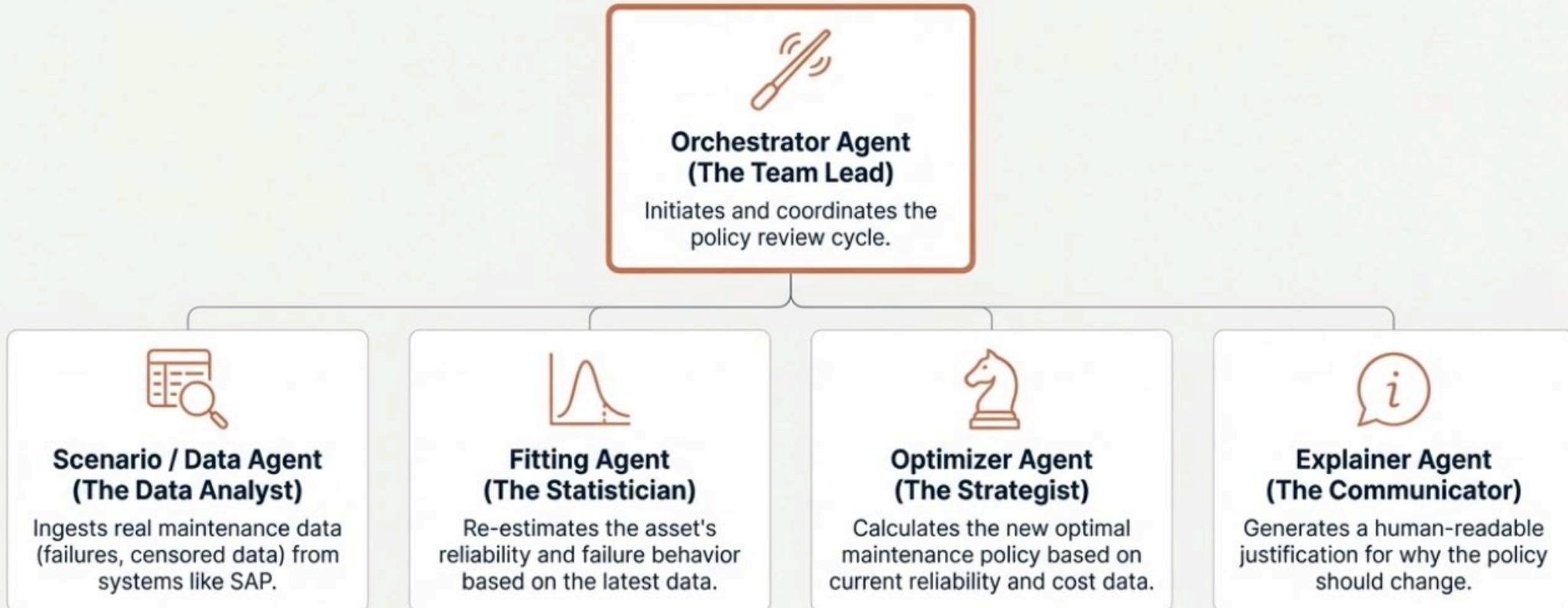
PART 3- THE AUTONOMOUS FRONTIER



- Asynchronous **message queue** decouples the agent from direct calls and enables event-driven operation.
- The **decision logic** is the core component responsible for evaluating the agent's current state, triggering transitions, and selecting appropriate actions.
- To make decisions, the agent can access **data repositories** (historical records, parameters, context) and invoke **analytical tools** that perform deterministic computations such as reliability estimation or optimization.
- Based on these results, the agent activates **action modules** that generate structured outgoing messages to other agents.
- Finally, **memory and learning components** store states, decisions, and outcomes, ensuring traceability and supporting adaptive behavior across conversations.

Meet Your Digital Maintenance Analyst Team

An Agentic AI system functions like a dedicated team of digital specialists, each with a clear role. They collaborate continuously to monitor, analyze, and govern maintenance policies in a closed loop, automating the entire policy review lifecycle.

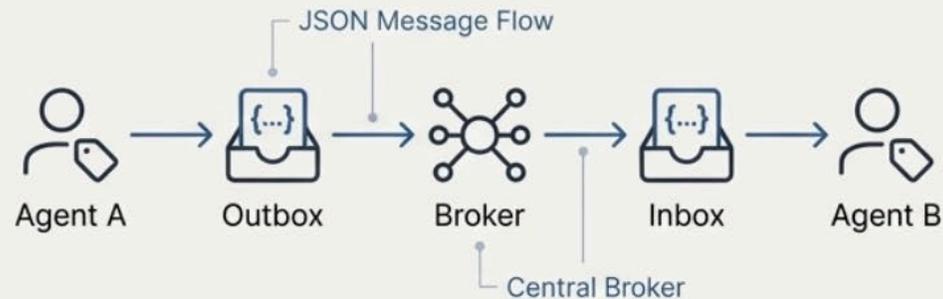


PART 3- THE AUTONOMOUS FRONTIER

All Interactions are Asynchronous and Traceable, Ensuring an Auditable Decision Record

Asynchronous Messaging

Agents communicate via structured JSON messages through a central broker. This design enforces loose coupling and emulates modern industrial event-driven architectures.



Tick-Level Traceability

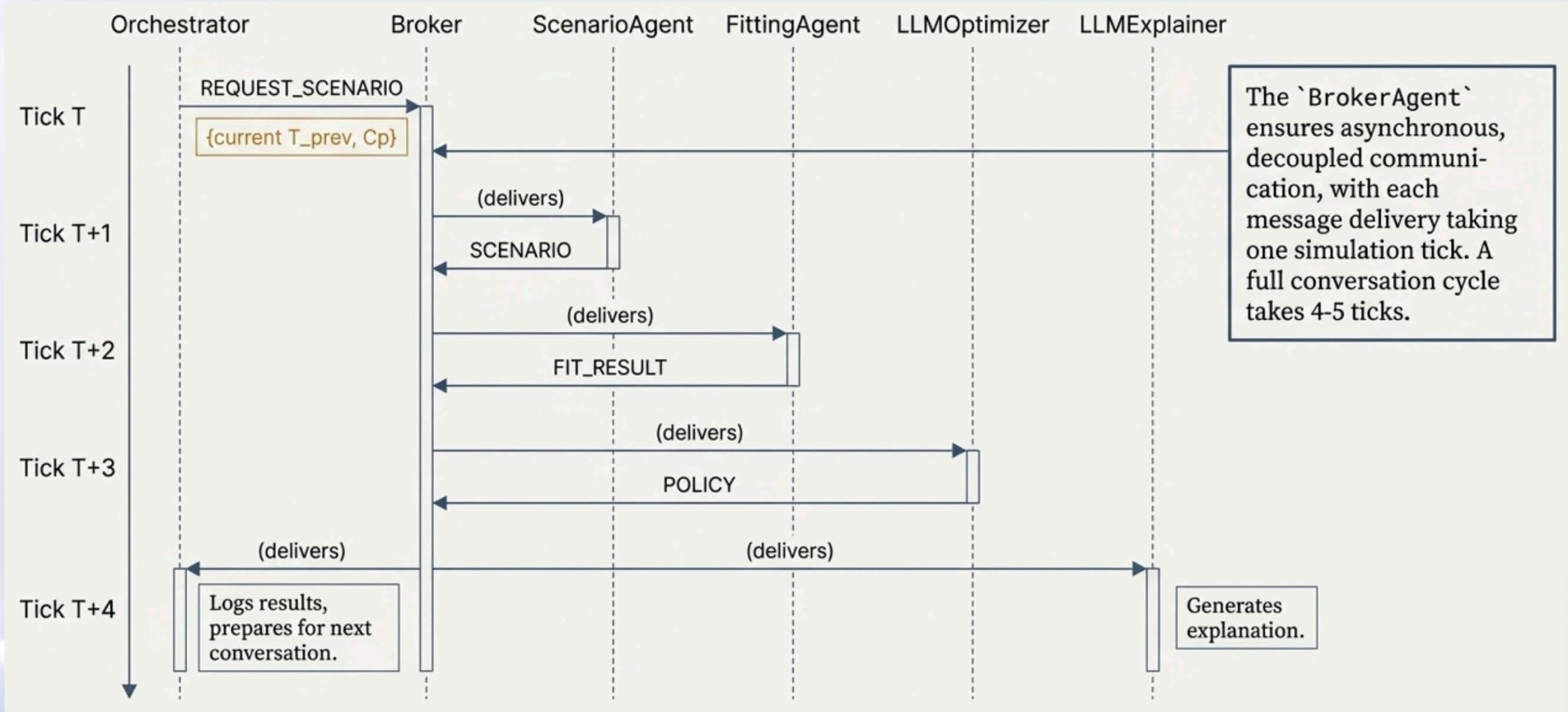
The system executes on a discrete timeline. Every action and message is time-stamped, allowing for a complete reconstruction of any policy decision.

```
TICK 1: Orchestrator -> REQUEST_SCENARIO
TICK 2: Broker -> Delivers REQUEST_SCENARIO
TICK 3: ScenarioAgent -> SCENARIO
TICK 4: Broker -> Delivers SCENARIO
...
```

This ensures that for any decision, we can precisely answer: Who knew what, and when?

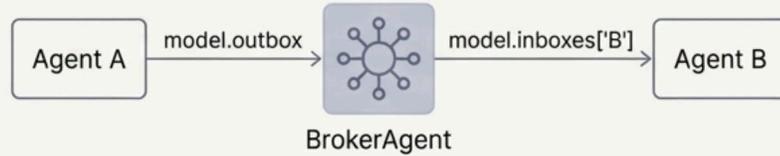
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BROKER AGENTS FOR AUTONOMOUS COMMUNICATIONS



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BROKER AGENTS FOR AUTONOMOUS COMMUNICATIONS



Agents are fully decoupled. They communicate exclusively by sending JSON messages through a central Broker.

The Broker introduces a one-tick delay, emulating real-world asynchronous communication networks.

```
{
  "sender": "orchestrator",
  "receiver": "scenario",
  "type": "REQUEST_SCENARIO",
  "conversation_id": "uuid-...",
  "timestamp": 1764952659.123,
  "payload": {
    "new_T_prev": 25.0,
    "Cp": 50.0
  }
}
```

Identifies the origin agent.

Specifies the destination agent.

Defines the purpose or action of the message.

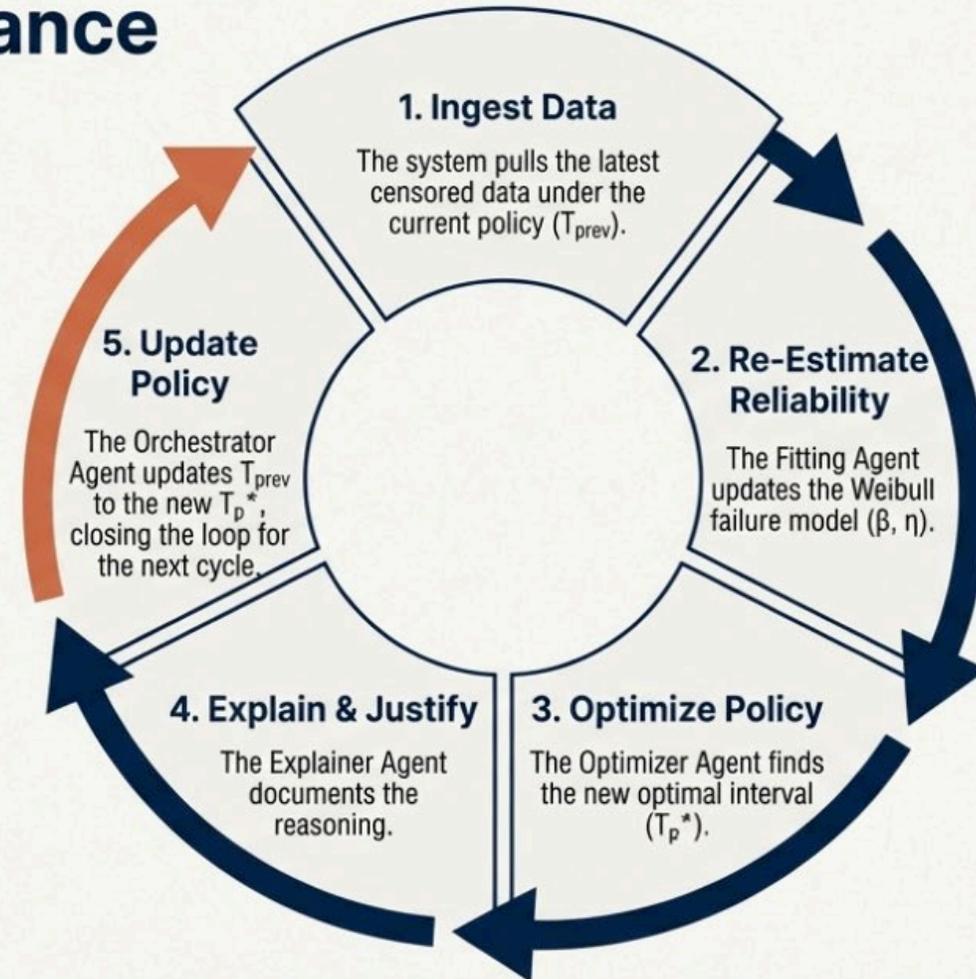
Contains the specific data and parameters for the task.

	Tick	Conv	Event(s)	
Each discrete time step (`tick`) is logged.	9	3	Orchestrator : starts conversation 3, T_prev=22.81, Cp=63.3	
	10	3	Scenario : generates scenario (conv 3), beta_true=2.00, T_prev=22.81	The one-tick message delay between agents is clearly visible.
	11	3	Fitting : fits Weibull, beta_hat=1.95, eta_hat=21.03	
	12	3	LLMOptimizer : policy=calendar_based, T_opt=21.55, Cp=63.3 LLMExplainer : generated explanation (policy=calendar_based...)	Multiple agents can act within the same tick.
	13	3	Orchestrator : ends conversation 3, policy=calendar_based, T_opt=21.55	

PART 3- THE AUTONOMOUS FRONTIER

The Autonomous Governance Loop: A System That Continuously Learns

Unlike a manual review, the agentic system operates in a persistent feedback loop. The policy decision from one cycle directly informs the data collected for the next, allowing the system to autonomously adapt to changes in failure regimes or economic conditions.



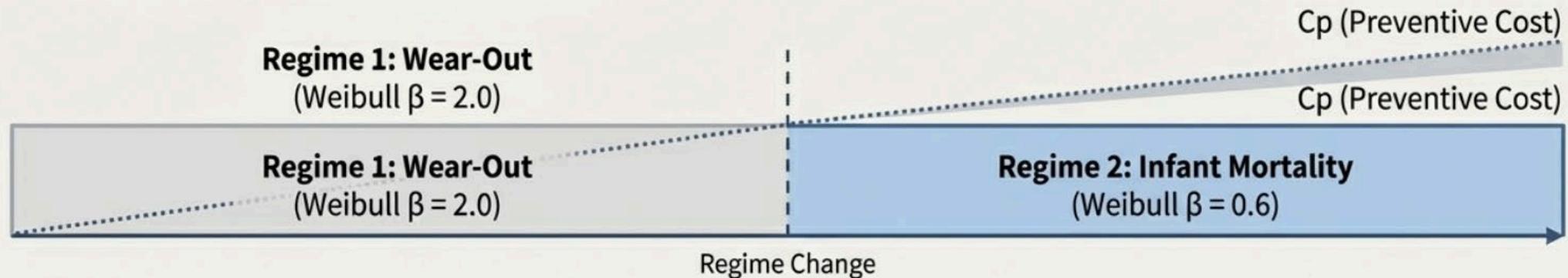
This is not a one-time analysis; it is an autonomous, repeatable, and auditable process.

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We Tested the System in a Dynamic Simulation Mirroring Real Industrial Challenges

The simulation environment introduces two sources of non-stationarity to test the system's adaptive behavior:

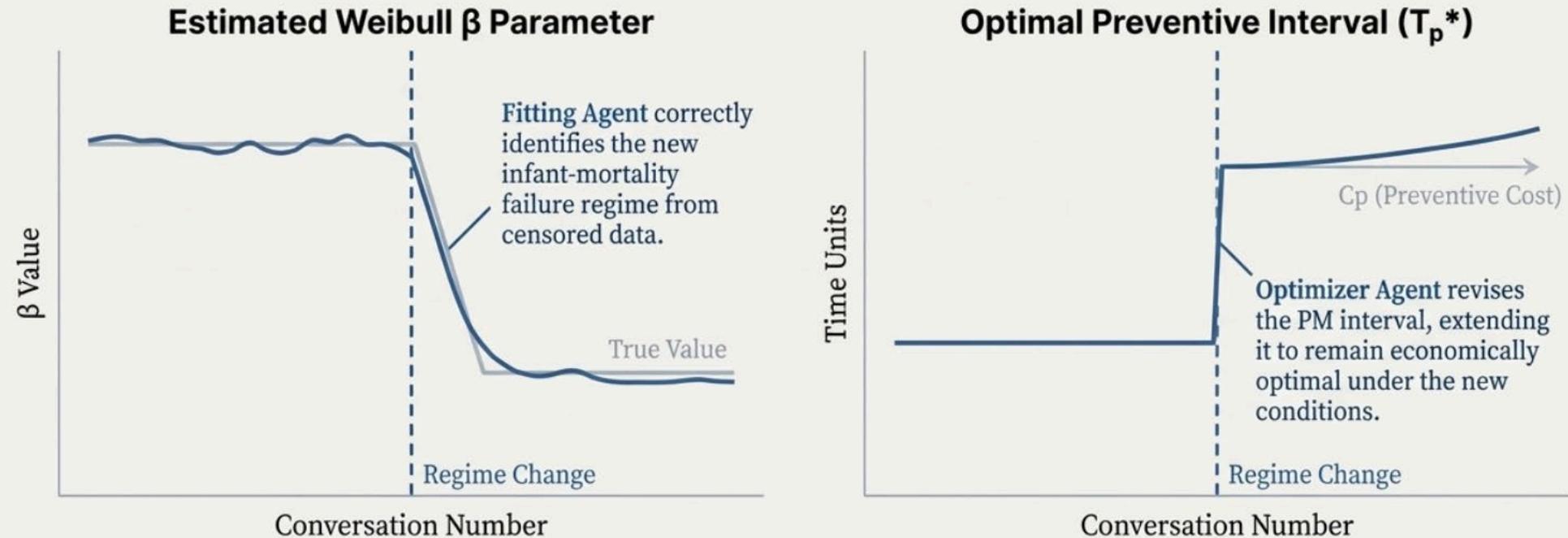
1. **Shifting Failure Regime:** Halfway through the simulation, the underlying failure behavior changes from a wear-out dominated regime to an infant-mortality dominated one.
2. **Evolving Cost Structure:** The cost of preventive maintenance (C_p) is progressively increased over time to reflect changing economic conditions.



Can the system autonomously adapt its maintenance policy when both the asset's physical behavior and its economic context are changing?

PART 3- THE AUTONOMOUS FRONTIER

The System Autonomously Detects Regime Changes and Adjusts Policy Accordingly



This demonstrates the system's capability to align policy with changing physical and economic realities in real-time.

PART 3- THE AUTONOMOUS FRONTIER

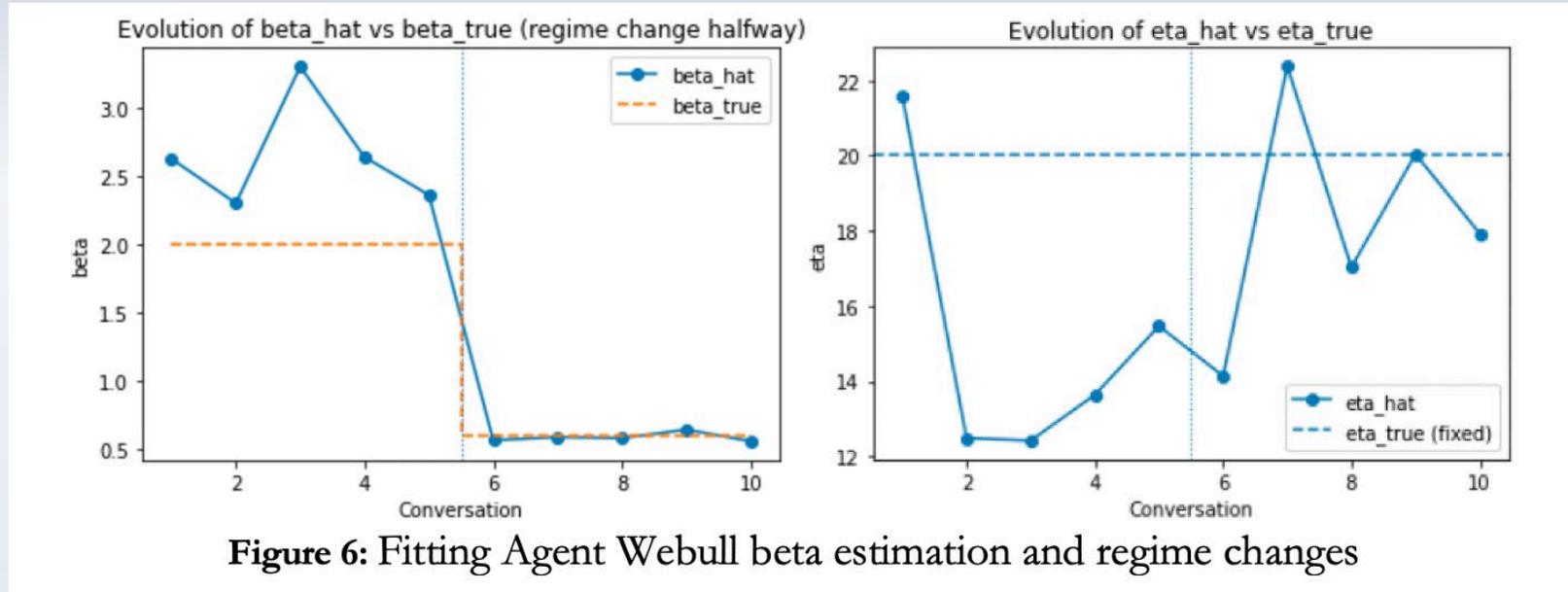


Figure 6: Fitting Agent Webull beta estimation and regime changes

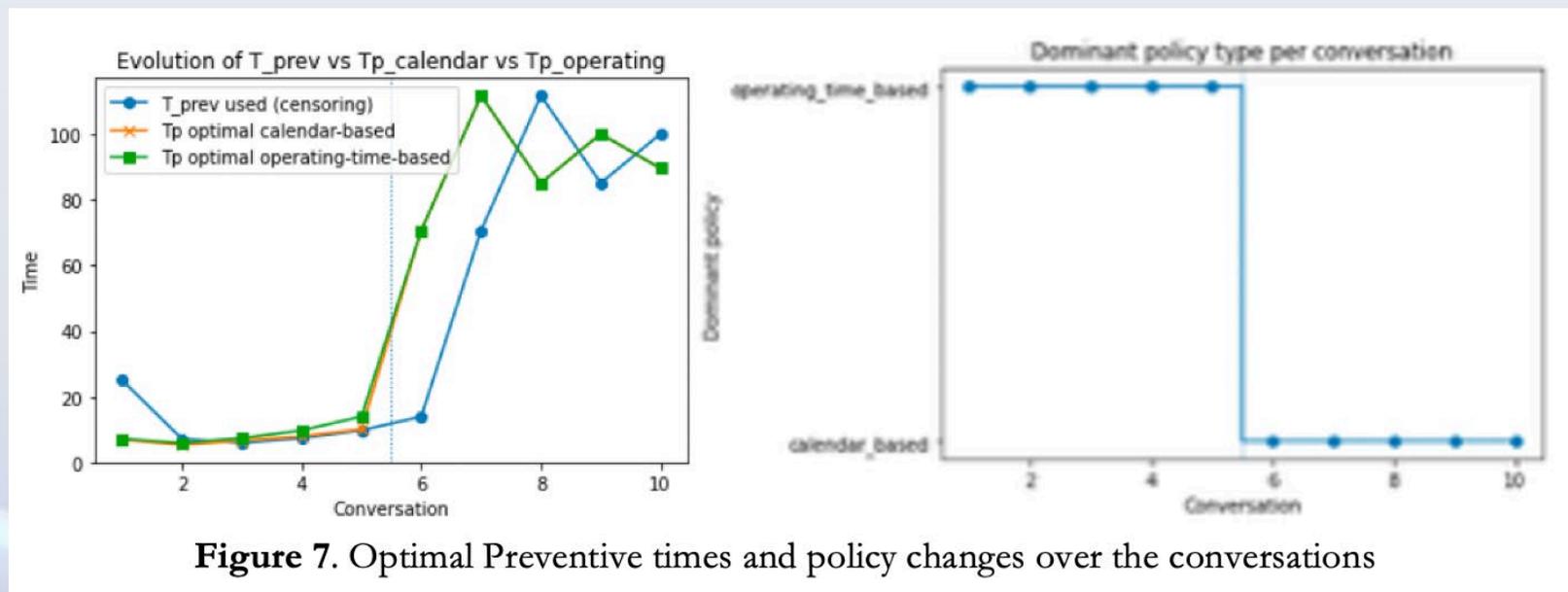
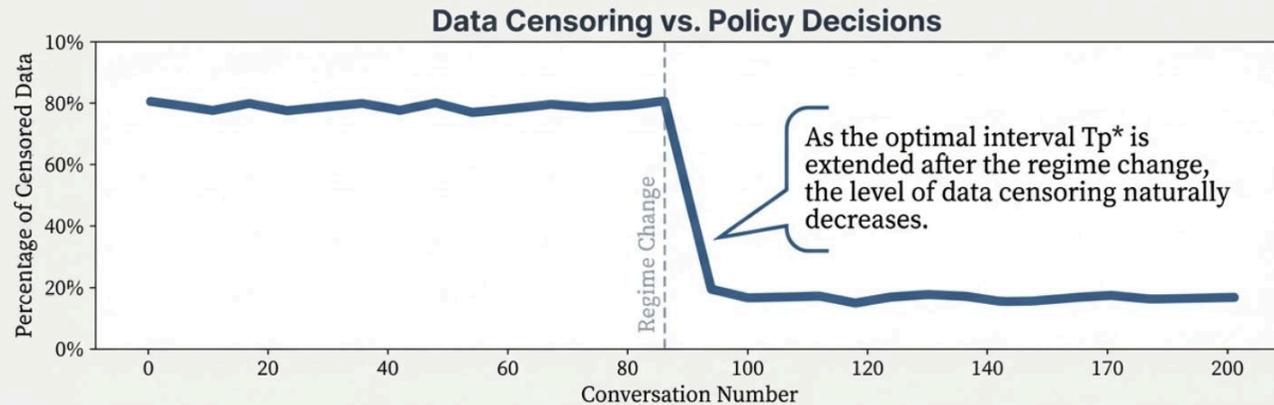


Figure 7. Optimal Preventive times and policy changes over the conversations

PART 3- THE AUTONOMOUS FRONTIER

The Policy Decision in One Cycle Directly Informs the Data for the Next

The system manages a critical feedback loop: the chosen PM interval (T_p) determines the censoring of the data, and that censored data is then used to re-estimate the reliability model that informs the next PM interval decision.



This demonstrates true adaptive behavior. The system is not just reacting to data; it is actively influencing the data it will see in the future through its own decisions.

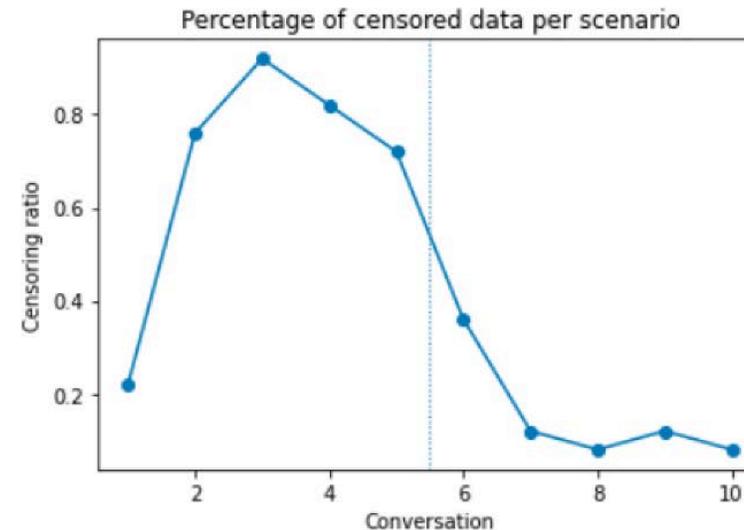
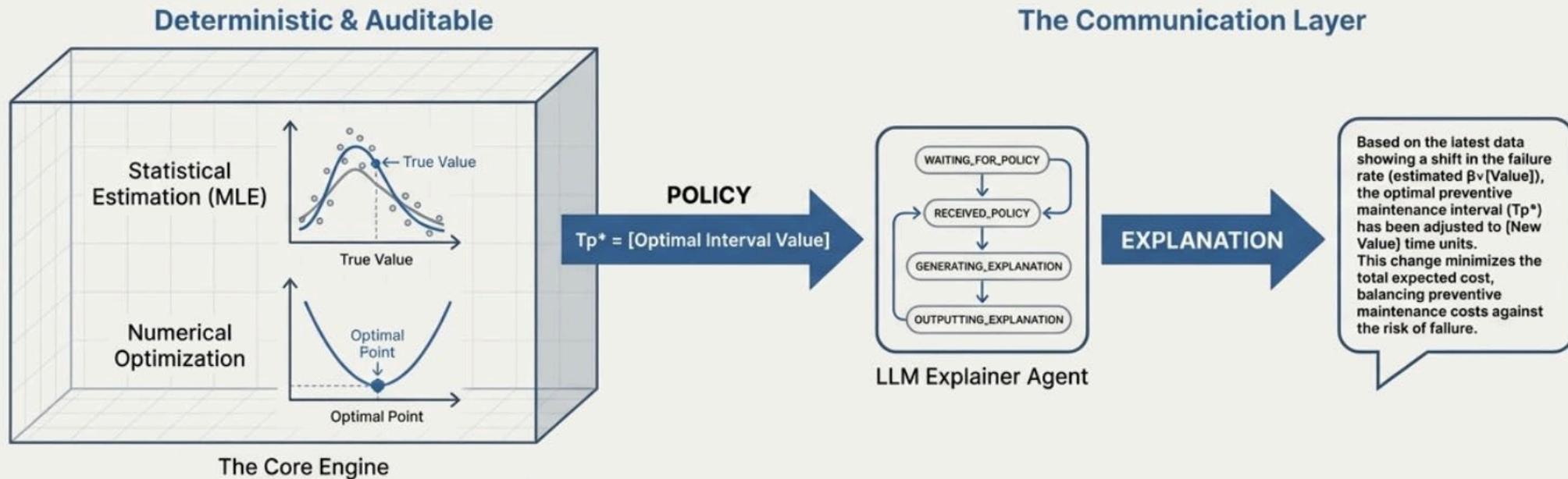


Figure 8. Censored data (%) showing adaptive behavior to PM policy changes.

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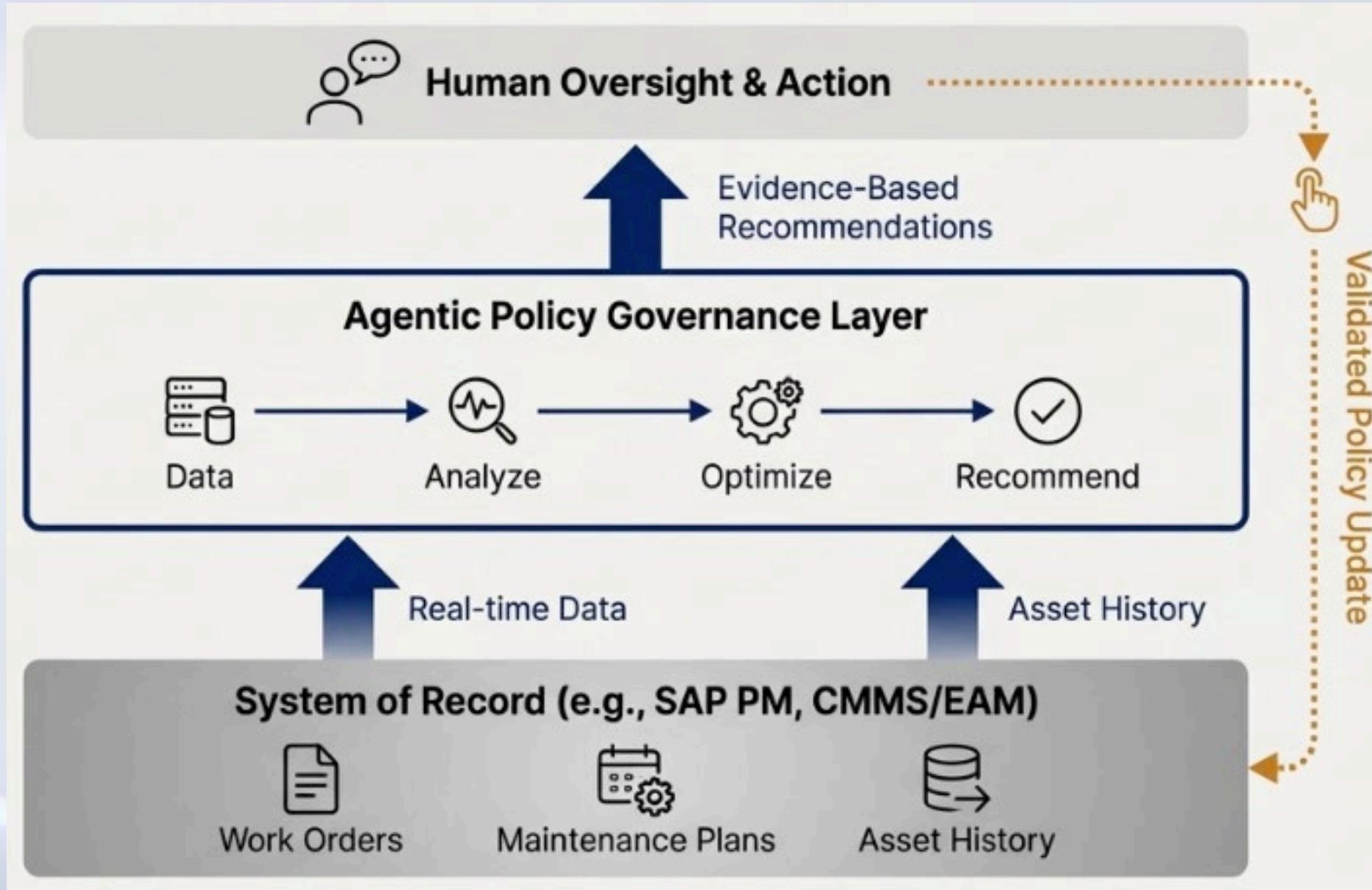
Deterministic Optimization Drives Decisions; LLMs Provide the Narrative

The system maintains a strict separation of concerns. Policy selection is computed exclusively through auditable statistical estimation and numerical optimization. LLMs are confined to translating this quantitative evidence into human-readable explanations.



“LLMs should act as interpreters and communicators rather than replacements for validated analytical models.”

PART 3- THE AUTONOMOUS FRONTIER



PART 3- THE AUTONOMOUS FRONTIER

Academic Agents Evolve into Robust Industrial Functions

Agent in Academic Model	Industrial Counterpart & Function
 Scenario Agent (Icon: Database/CMMS)	CMMS Data Agent: Ingests and cleans real work orders and failure histories from SAP PM or other EAMs.
 Fitting Agent (Icon: Magnifying glass over curve)	Fitting Agent: Performs Weibull MLE on real-world censored data to capture actual degradation patterns.
 Optimizer Agent (Icon: Calculator/Gears)	Optimizer Agent: Uses real preventive (C_p) and corrective (C_c) costs from the plant to recommend interval adjustments.
 Orchestrator Agent (Icon: Conductor's baton)	Orchestrator Module: Schedules periodic policy evaluations (e.g., weekly, monthly) and coordinates the end-to-end workflow.
 Explainer Agent (Icon: LLM/Chat bubble)	LLM Module: Generates audit-ready, natural-language justifications for engineers, managers, and regulators.

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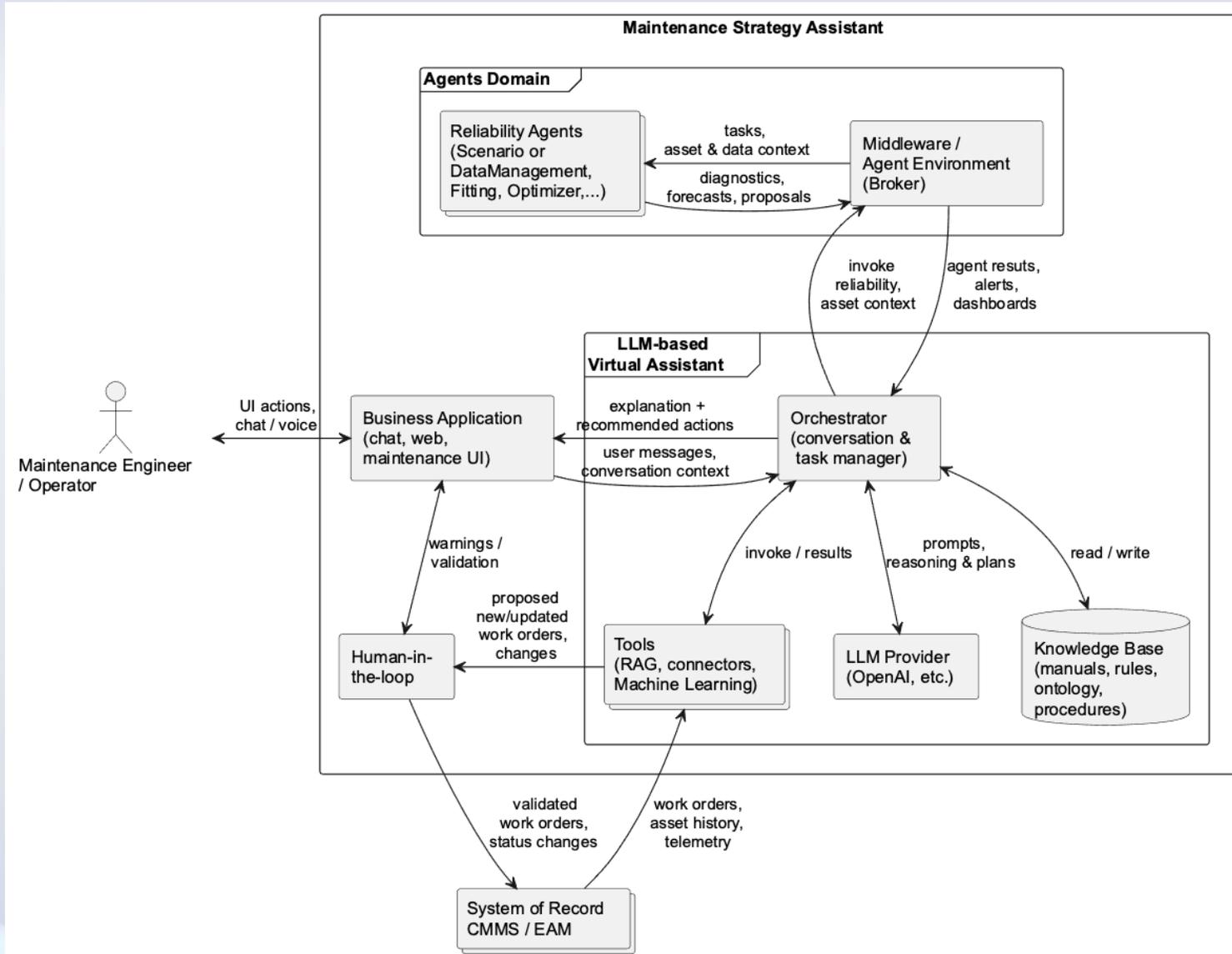


Figure 9. Reliability Agentic AI Architecture

PART 3- THE AUTONOMOUS FRONTIER

Conversation with ACM
07/12/2025 · Closed

This conversation is closed
Conversation duration 2:37

Virtual Reliability Assitant:
Hello!. Good afternoon. How can I help you? 16:06

User ACM:
Good afternoon! I'm a reliability analyst, and I'd like to review the preventive maintenance policy for electrical transformers. Can you tell me whether it is calendar-based or operating-time-based? 16:07

Virtual Reliability Assitant:
Please wait a moment! 16:07

User ACM:
No problem. 16:08

Virtual Reliability Assitant:
The dominant policy in electrical transformers is Operating-Time Based. The current Weibull parameters are beta_true 0.6 and beta_hat 0.72, with $C_p = 190.0$ and $C_c = 250.0$ as operating costs, resulting in $T_{p^*} = 45.3$. 16:08

Virtual Reliability Assitant:
Please note that the next automatic review of this policy is scheduled on 15/01/2026, with an annual updated period. 16:08

Virtual Reliability Assitant:
Do you need any more information? 16:08

User ACM:
No, thank you very much. 16:08

Virtual Reliability Assitant:
Ok, whenever you need, I'm here. 16:08

AI Assistant:
1 recommendation

Explanation:
The optimization process balances the relatively high corrective cost against the lower preventive cost, using the fitted Weibull parameters to estimate the expected failure behaviour under different intervals. The dominant policy is selected because it yields the lowest expected cost per unit time when considering both planned interventions and unplanned failures. The chosen preventive interval reflects a compromise: short enough to significantly reduce the probability and impact of corrective interventions, but not so short that preventive actions become excessively frequent and costly. 16:08

Recommendations:

- Provide additional information on the inputs required to calculate the optimal value.
- Explain the steps involved in the optimization process.
- Confirm whether the user has added any equipment in the last 12 months.

Required Entities:

- Confirm whether it is added any equipment in the last 12 months.
- Ask whether they need more information about the process.

16:08

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Autonomous Governance Transforms Maintenance from a Static Cost Center to a Dynamic, Strategic Function

From Static Documents to Living Artifacts

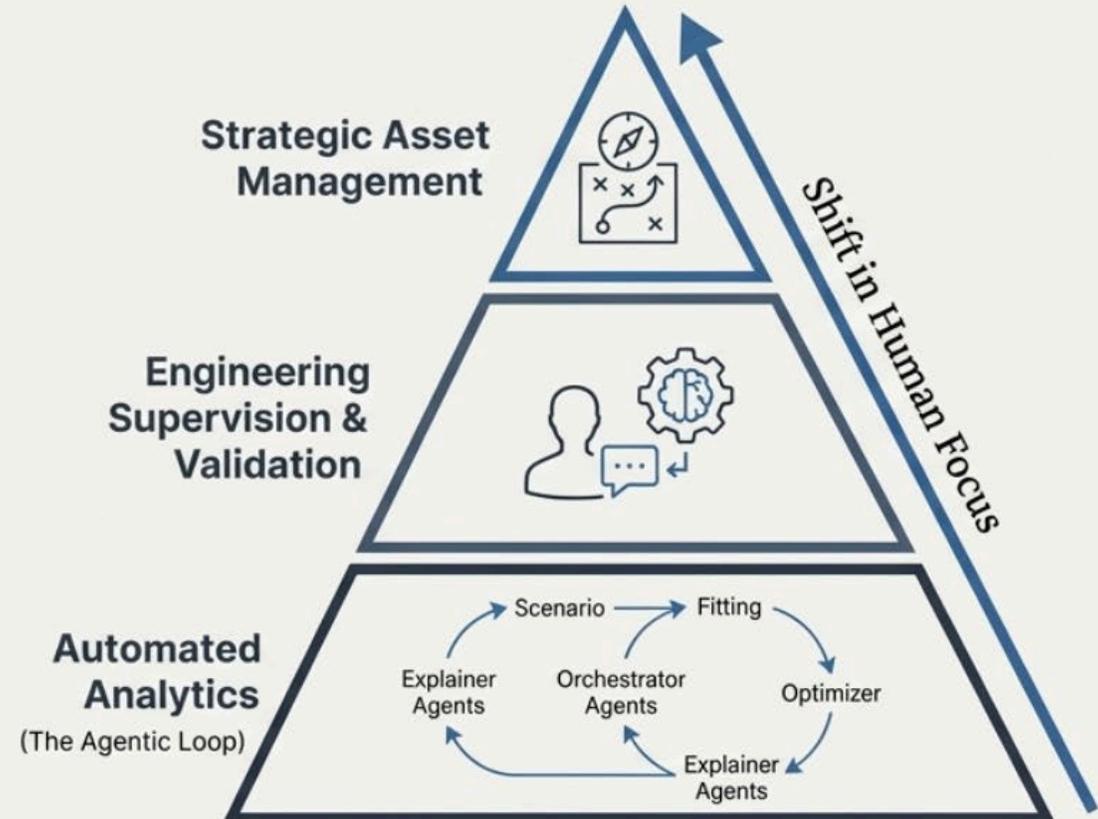
PM policies are no longer fixed but are continuously validated against real-world evidence.

From Repetitive Analysis to Strategic Supervision

Frees reliability engineers from manual recalculations to focus on higher-level goals like risk management, system-level optimization, and alignment with business objectives.

From Historical Precedent to Evidence-Driven Justification

Every policy decision is backed by a transparent, auditable trail of data, models, and economic reasoning, supporting governance and regulatory compliance.



Key Takeaways and Conclusions



- Digital transformation is a necessary foundation, not the end goal. Data connectivity enables visibility, but **value is created only when data is transformed into intelligence.**
- Intelligent maintenance evolves into a continuous, **value-driven process aligned with business objectives.**
- AI augments human expertise before replacing decisions. AI-assisted strategies enhance planning, prioritization, and optimization while keeping humans in the loop.
- **The real breakthrough comes with autonomous governance.** Agent-based AI systems enable continuous policy execution, learning, and adaptation at scale.
- From tools to systems: **intelligence emerges from orchestration.** Value is generated when data, analytics, agents, and governance mechanisms work as an integrated ecosystem.
- **The future of maintenance is adaptive, explainable, and self-improving.** Intelligent systems must learn from outcomes, ensure traceability, and evolve with asset and business contexts.
- **Organizations that master this transition will gain sustainable competitive advantage.** Intelligent maintenance directly impacts availability, cost efficiency, risk reduction, and long-term resilience.



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THANK YOU!



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