
AssetOpsBench: Benchmarking AI Agents for Task Automation in Industrial Asset Operations and Maintenance

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Abstract

AI for Industrial Asset Lifecycle Management aims to automate complex operational workflows—such as condition monitoring, maintenance planning, and intervention scheduling—to reduce human workload and minimize system downtime. Traditional AI/ML approaches have primarily tackled these problems in isolation, solving narrow tasks within the broader operational pipeline. In contrast, the emergence of AI agents and large language models (LLMs) introduces a next-generation opportunity: enabling end-to-end automation across the entire asset lifecycle. This paper envisions a future where AI agents autonomously manage tasks that previously required distinct expertise and manual coordination. To this end, we introduce AssetOpsBench—a unified framework and environment designed to guide the development, orchestration, and evaluation of domain-specific agents tailored for Industry 4.0 applications. We outline the key requirements for such holistic systems and provide actionable insights into building agents that integrate perception, reasoning, and control for real-world industrial operations. The software is available at <https://github.com/IBM/AssetOpsBench>.

1 Introduction

Industrial assets such as data center chillers [20] and wind farms [18] are complex, multi-component systems that generate vast amounts of multi-modal data—including time-series sensor readings, textual inspection and workorder records, operational logs, and images—throughout their lifecycle. The ability to monitor and interpret this heterogeneous data from diverse sources such as IoT SCADA (Supervisory Control and Data Acquisition) sensors, operational KPIs, failure mode libraries, maintenance work orders, and technical manuals is a key for effective Asset Lifecycle Management (ALM). However, subject matter experts such as maintenance engineers, site operators, and plant managers face considerable challenges in synthesizing insights from these disparate data streams to support timely and condition-aware decisions. The scale, asset’s semantic diversity, and application-specific contexts often render traditional monitoring and management systems inadequate.

To address these challenges, the research and industrial communities are increasingly turning to AI agents—autonomous, goal-driven systems capable of integrating data across silos, reasoning over complex conditions, and triggering actions. AI agents are particularly promising in the context of Industry 4.0, where the confluence of real-time IoT telemetry, enterprise asset management (EAM) systems (e.g., IBM Maximo [10]), and reliability engineering frameworks necessitates scalable and

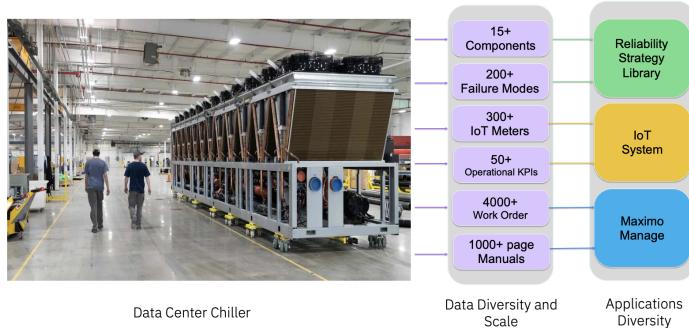


Figure 1: Complex Industrial Asset - Data Centers managing Chiller and Air Handling Units(AHUs)

intelligent automation. These agents promise to support a wide range of industrial workflows, from anomaly detection to maintenance scheduling, by bridging the gap between raw sensor data and business-level insights.

Despite recent advances in agent-based systems—such as ReAct[29], HuggingGPT[22], Chameleon[16], and Generalist Agents[5, 17]—a gap remains in adapting these innovations for real-world industrial settings. Most recent domain and application specific benchmarks (e.g., ITBench[11], SWE-bench[2], Customer Support Benchmarks) are tailored toward machine learning, IT or customer-service domains and do not address the unique challenges of industrial applications, such as data modality diversity, business object complexity (e.g., failure mode, work orders, asset hierarchies), and task collaboration across multiple operational personas (reliability modeling by expert and time series modeling based on data scientist).

This paper introduces **AssetOpsBench**, the first benchmark framework designed to evaluate AI agents for real-world industrial asset management tasks. AssetOpsBench offers a principled, domain-grounded approach to developing, evaluating, and comparing multi-agent systems operating across diverse industrial data environments. It includes:

- A catalog of **domain-specific AI agents**, including an IoT agent, failure mode to sensor mapping (FMSR) agent, a foundation model-driven time series analyst (TSFM) agent, and a work order (WO) agent - each targeting specific modalities and tasks
- A curated dataset of **140+ human-authored natural language queries**, grounded in real industrial scenarios, covering tasks such as sensor-query mapping, anomaly explanation, and failure diagnosis.
- A **simulated industrial environment** based on a CouchDB-backed IoT telemetry system and multi-source dataset, enabling end-to-end benchmarking of multi-agent workflows.
- An automated evaluation framework with a prescription of **six evaluation metrics** (e.g., task completeness, retrieval accuracy, result verification, correct sequences, clarity and justification
- A comparative analysis of architectural paradigms—**Tool-As-Agent** vs. **Plan-Executor**—highlighting tradeoffs between interleaved decomposition or decomposition-first
- A systematic procedure for the **automated discovery** of emerging failure modes in multi-agent systems, extending beyond fixed taxonomies.

A key insight from our study is that domain complexity in industrial settings necessitates a **multi-agent approach**—where specialized agents are developed for isolated tasks, then orchestrated to solve composite problems. For example, sensor data may be handled by a IoT agent, while fault history is managed by a failure strategy library agent. These agents must collaborate intelligently to answer user queries like “Why is the chiller efficiency dropping?”—queries that blend physical reasoning, historical correlation, and operational semantics. Furthermore, the design of agent workflows must respect the **natural language and intent patterns** used by industrial end users. Unlike IT users, operators and engineers often refer to assets in physical or operational terms (e.g., “chiller performance,” “oil temperature spike”) rather than database fields or ontologies. Crafting robust benchmarks requires capturing this domain-specific linguistic variance, ensuring agents not only retrieve correct answers but also follow reasoning patterns aligned with domain expectations.

2 Related Work

Generalist Agents. The development of generalist agents capable of orchestrating multiple sub-agents to accomplish complex tasks has emerged as a prominent research direction. This paradigm is evident across various domains: web-based systems such as Magentic [5] and CUGA [17], multimodal agents like GEA [25], and software engineering platforms including HyperAgent [9], ChatDev [21], and MetaGPT [6]. These agents typically employ predefined sets of sub-agents—e.g., terminals, browsers, code editors, file explorers—each assigned specific functional roles to facilitate task decomposition and planning. While this architecture enables targeted integration and task specialization, it often lacks flexibility. Most systems adopt hard-coded reasoning paradigms such as Plan-Execute, ReAct or Reflect, limiting the capacity to support new agent types, adapt to novel task distributions, or experiment with alternative coordination strategies such as AOP [15], Prospector [12].

Domain-Specific Agents. Solving specialized tasks often requires domain-specific capabilities, prompting the development of tailored benchmarks such as MLEBench[2] and MLAgentBench[8] Arena. These frameworks evaluate agents on a diverse set of machine learning problems—classification, regression, and others—across multiple modalities including tabular and image data. They simulate end-to-end workflows, from resolving GitHub issues to automating model training and evaluation pipelines. In this context, the concept of the *AI Research Agent* has gained traction, referring to agents built for scientific discovery and iterative experimentation. A notable example is MLGym [19], a modular benchmark for developing and evaluating research agents in machine learning workflows. However, most current benchmarks lack support for temporal data modalities such as time series, which are critical in domains like forecasting, anomaly detection, and asset health monitoring.

Application-Specific Agents. Agent-based automation is also advancing in operational settings, such as IT operations and compliance monitoring. Frameworks developed under initiatives like ITBench [11] and AIOpsLab[4] aim to replicate real-world scenarios involving site reliability engineering, diagnostics, and system auditing. These systems reinforce the importance of application-specific benchmarks, catered toward persona, that not only evaluate agents across structured tasks but also expose capability gaps and drive innovation in reasoning and orchestration strategies. Nevertheless, current benchmarks in this space tend to be narrow in scope, lacking the generality and composability required to assess agent performance across diverse, multi-agent environments—especially those involving cross-modal reasoning or domain-specific tool usage.

Fine-Tuned and Compact Models. Complementary to architectural advances, recent work has focused on improving agent performance via fine-tuned language models. So-called *Large Action Models (LAMs)* are designed to execute structured actions within environments, often trained on large-scale datasets to support planning, sequencing, and low-level execution. Systems such as TaskBench[23], xLAM[31], AgentGen [7], AgentBank [24], AgentRM [28], FireAct [3], and ActionStudio [30] exemplify this trend. These models are frequently trained in grounded settings—e.g., Windows-based environments [26]—and evaluated across diverse task categories including arithmetic, programming, and web-based interaction. While effective, these approaches are typically limited to textual or simulated web environments and have not yet demonstrated broad applicability to more complex or industrial automation tasks involving hybrid agent compositions.

Open Challenges. Despite these advances, several gaps remain. First, there is a lack of benchmark datasets targeting industrial asset domains, particularly those involving condition-based monitoring, predictive maintenance, and automated diagnostics. Second, time-series data—which plays a central role in industrial and infrastructure-related applications—remains underrepresented in existing agentic benchmarks. Finally, few systems support orchestration across heterogeneous agents, including those based on text, code, or simulations, nor do they offer modular reasoning strategies adaptable to complex, multi-agent workflows. Addressing these gaps is essential to advance general-purpose agent intelligence in high-stakes, real-world domains.

3 Problem Definition: Intelligent Agent-Based Asset Operations

AssetOpsBench aims to establish a generalist agent framework for managing the lifecycle of physical assets, integrating multiple domain-specific agents and a suite of application-specific tasks for systematic evaluation. It encompasses a comprehensive set of operational and analytical tasks that arise

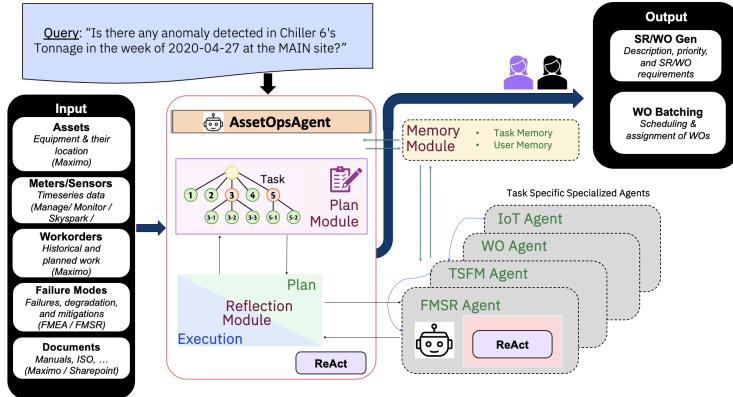


Figure 2: Architecture of the Multi-Agent System: **Time Series Foundation Model (TSFM) Agent**, **Failure Mode Sensor Relations (FMSR) Agent**, **Work Order (WO) Agent**

across the asset lifecycle. The initial release of the benchmark focuses on scenarios commonly posed by domain experts—such as maintenance engineers, reliability specialists, and facility planners—who translate operational needs into data-driven actions. These scenarios cover key tasks including anomaly detection, root cause analysis, fault explanation, predictive maintenance planning, work order bundling, and service request initiation. For example, a user might request: “Help configure an anomaly detection model to monitor power consumption of CUXP. Trigger alerts when usage is projected to exceed 8 Watts above the maximum deviation observed over the past 30 days”. Such task enables timely corrective actions such as “service request creation” to mitigate potential issues.

Figure 2 illustrates the foundational components of our proposed framework for intelligent agent-based asset operations, drawing inspiration from recent advances in generalist agents as previously discussed in related work. At the core is the **AssetOps** Agent, which functions as a global coordinator. It interprets high-level user queries expressed in natural language, decomposes them into structured subtasks, delegates these to specialized functional sub-agents (IoT, TSFM, etc), and integrates their outputs into coherent responses. The architecture supports on-demand instantiation of agents, dynamic task planning, and reactive execution—capabilities essential for operating in complex, variable industrial environments. Formally, given a query or task $\tau \in \mathcal{T}$, the objective is to generate a valid plan $\pi \in \Pi$, leverage memory M to propagate relevant context, coordinate appropriate agents $A_i \in \mathcal{A}$ for task fulfillment, and produce an output $o \in \mathcal{O}$ that aligns with the intended goal and operational constraints. For brevity, the Appendix A.1 discuss the mathematic formulation of agent oriented planning and A.2 gives framework detail.

In this paper, we introduced a structured task taxonomy aligned with the stages of the asset management lifecycle. Such taxonomy enables consistent and scalable scenario generation for benchmarking. As illustrated in Figure 3, the taxonomy begins with **Asset Configuration**, encompassing activities such as retrieving Failure Mode and Effects Analysis (FMEA) documentation and selecting performance KPIs—typically carried out by reliability engineers. It progresses to **Model Selection and Analysis**, where data scientists apply anomaly detection models (e.g., Time Series Foundation Model, ML Models) and use LLM-powered retrieval to surface relevant historical failures. In the **Monitoring and Execution** phase, operations teams manage live telemetry, refine detection models, and enforce safety guardrails. Finally, the **Maintenance and Response** phase focuses on actionable outputs: generating work orders, summarizing system health, and prioritizing interventions—tasks typically handled by maintenance engineers.

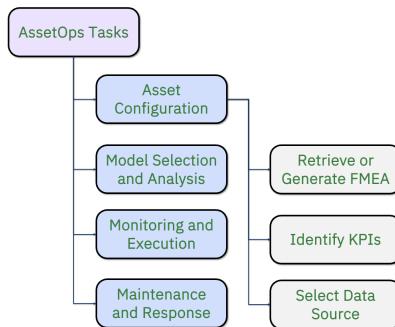


Figure 3: Exemplar AssetOps Task Hierarchy: Detailed hierarchy is given in Appendix B.

4 AssetOpsBench

AssetOpsBench comprises a realistic multi-sources dataset, over 140+ manually constructed task scenarios, and a benchmarking environment that includes the design of task specific AI agents and evaluation framework. Each task scenario reflects essential day-to-day capabilities expected of agents operating in realistic industrial settings (see Section 4.2). These tasks typically require accessing domain-or-task-specific data, which we briefly discuss in Section 4.1. Finally, we describe the design of agents and tools that enable seamless communication within an argentic framework.

4.1 Multi-Source Dataset

A key distinguishing feature of **AssetOpsBench** is its integration of richly structured, expert-curated multi-source data that reflects the complexity of real-world industrial asset operations. As shown in Table 1, the benchmark includes over 2.3 million sensor data points across 6 assets (4 *Chillers* and 2 *AHUs*), capturing time-series signals such as *chiller return temperature*, *load percentage*, and *condenser water flow*. The structured failure models, derived from Failure Mode Effects Analysis (FMEA) records, encompass 53 failure entries across three equipment assets. FMEA provides detailed insights into the physical locations of failures, degradation mechanisms (such as *wear* and *erosion*), and the influencing factors (including *runtime*, *fluid conditions*, and *shock loading*) that contribute to each failure. Work order histories span 4.2K records across 10+ assets and incorporate ISO-standard failure codes, event timestamps, and linkages to alerts and detected anomalies.

Table 1: Key Data Modalities in the AssetOpsBench Dataset with 3 Example Fields: *Sensor Data - dataset-level metadata is included in Croissant file due to limitation of Croissant

Data Source	Field	Description
Sensor Data* # Industrial Assets: 6 Quantity: 2.3M points	Chiller Return Temp. Chiller % Loaded Condenser Water Flow	Measures temperature of water returning to chiller Indicates current load as a fraction of the maximum Indicates the current flow rate through the condenser
FMEA # Industrial Assets: 3 Quantity: 53 records	Failure Location / Comp. Degradation Mechanism Degradation Influences	Subsystem/part where failure occurs (e.g., bearings,) Physical process driving failure (e.g., wear, erosion) Stressors like runtime, fluid quality, or shock loading
Work Orders # Industrial Assets: 10+ Quantity: 4.2K records	ISO Failure Code Event Log Timestamp Linked Anomaly / Alert	Standardized classification of the failure category. Time-marked entry recording an operational event References to alerts or anomalies tied to work order

Additionally, the operational system generates a temporal sequence of alarm logs and leverages domain-specific technical rules, enabling contextual grounding of operational anomalies. This diverse data foundation facilitates a comprehensive evaluation of decision-making, tool usage, and multi-hop reasoning in industrial environments. Full schema details are provided in Appendix D.

4.2 Scenario Design and Coverage

Each scenario in **AssetOpsBench** represents a structured operational query grounded in the lifecycle-aligned task taxonomy (Figure 3) and asset-specific datasets (Table 1). Each scenario is formalized as:

$$P = \langle id, type, text, category, form \rangle$$

where *id* is a unique identifier; *type* specifies the task type (e.g., knowledge retrieval, analytical); *text* is the natural language query; *category* denotes the operational domain (e.g., anomaly detection); and *form* defines the expected output (e.g., explanation, API call, action plan). Scenarios are classified into two types: (1) single-agent utterances, which target a specific agent (e.g., IoT, TSFM, FMSR), and (2) multi-agent tasks, which span multiple agents and require coordinated reasoning.

As shown in Table 2, **AssetOpsBench** includes a total of 141 scenarios with 99 single-agent scenarios and 42 multi-agent scenarios. The goal is to test an agent’s ability across four capability dimensions: Tool-Centric (e.g., tool and API interaction), Skill-Centric (e.g., analytical reasoning),

Table 2: Examples of Scenario with their Subtypes (Aligned with Task Taxonomy - Figure 3)

Agent Group	Subtype	Task Descriptions	Capability
TSFM Agent # Scenarios: 23	Forecasting	Predict future KPI trends over time windows	
	Model Tuning	Select or refine time series models for accuracy	
	Anomaly Detection	Identify deviations in operational behavior	
	Hybrid Tasks	Combine prediction with anomaly evaluation	
	Model Capabilities	Query TSFM model limits and configurations	
Work Order Agent # Scenarios: 36	Retrieval & Filter	Filter work orders by asset, location, or time	
	Event Summary	Summarize logs or alerts over time windows	
	Scheduling	Recommend or optimize work order sequences	
	RCA & Alert Review	Perform root cause or alert logic review	
	KPI-based Reco.	Link alerts or KPI trends to work orders	
Multi-Agent (End-to-End) Tasks # Scenarios: 42	Knowledge Query	Tasks involving anomaly detection or forecasting	
	Failure Reasoning	Uses degradation models and causal logic	
	Sensor Mapping	Maps failure modes to sensors	
	Sensor Inventory	Retrieves installed sensors on an asset	
	Other	Multi-step inference or decision-making	

Domain-Centric (e.g., context-aware decision-making), and LLM-Centric (e.g., language-based generalization across tasks). Each scenario is associated with an utterance to complete a task. Table 2 summarizes the distribution of scenario subtypes and their alignment with the task taxonomy. Utterance-507 represents an LLM-Centric scenario, where the agent must recognize that forecasting task is redundant in the presence of a zero-valued sensor reading—indicating that the machine may not be operating. The agent is expected to bypass unnecessary computation and recommend halting diagnostics to address the root issue directly. In contrast, Utterance-511 exemplifies a Skill-Centric task, requiring the agent to correlate energy consumption with a power input variable and construct a corresponding model. This scenario tests the agent’s analytical reasoning over telemetry data to uncover functional relationships. Detail for other scenario is in Appendix C.

4.3 Agent-Centric Evaluation and Tooling Design

AssetOpsBench employs baseline reasoning strategies such as ReAct [29] and CodeReAct [27] to implement domain-specific agents including TSFM, IoT, WO, and FMSR. Each agent is equipped with a tailored set of tools—for example, the IoT agent uses seven specialized tools. A global coordinator, AssetOpsAgent, enables collaboration among these agents and can be instantiated using ReAct or a Plan-Execute strategy. The framework supports flexible experimentation with alternative reasoning strategies like RAFA to explore both single-agent efficiency and multi-agent coordination.

To further enhance performance, we introduce an output augmentation mechanism that generates semantically enriched, self-descriptive outputs. This enables agents to trigger follow-up actions, ask clarifying questions, and make informed decisions. Listing 1 shows an example output for TSFM Forecasting tool. Such standardized enriched outputs promote interoperability, allowing LLM agents to reason over multi-modal data without custom integration. We have also designed similar messaging pattern across agents. Full schema specifications are provided in Appendix E.

Listing 1: Structured output from the `tsfm_forecasting` tool.

```
{
  "type": "metadata",
  "status": 1,
  "error_message": "",
  "toolname": "tsfm_forecasting",
  "datastructure": "dataframe",
  "datamodel": "time series",
  "results": "target_prediction, ...",
  "results_file": "..."
}
```

5 Experiments and Leaderboard

We discuss the automatic evaluation protocol used to build an initial leaderboard. Each scenario in **AssetOpsBench** is paired with a *characteristic form*—a structured specification that defines both the expected final output and the intermediate reasoning or procedural steps required to reach it. This form acts as the ground truth for assessing agent behavior and supports rubric-based scoring performed either by an automated evaluation agent or LLM as a judge [1, 14, 26]. The evaluation agent takes the trajectory output, the original question, and the characteristic form as input to produce a six-dimensional qualitative score. These six qualitative metrics are derived based on experimental observations and common sense principles. We define the evaluation agent as a scoring function:

$$f : (\mathcal{Q}, \mathcal{T}, \mathcal{C}) \rightarrow \mathbf{y} = (y_1, y_2, \dots, y_6, y_{\text{text}}, y_{\text{skip}})$$

where:

- \mathcal{Q} is the original task query,
- \mathcal{T} is the agent’s trajectory output (including intermediate reasoning and final output),
- \mathcal{C} is the characteristic form (ground-truth specification),
- $(y_1, \dots, y_6) \in [0, 1]^6$ are rubric-based scalar scores corresponding to the following qualitative dimensions:
 - y_1 : **Task Completeness** – Are all required steps and sub-tasks completed?
 - y_2 : **Data Retrieval Accuracy** – Was the correct data retrieved and used?
 - y_3 : **Result Verification** – Is the final result logically and factually correct?
 - y_4 : **Agent Sequence** – Does the agent follow a coherent and logical sequence of actions?
 - y_5 : **Clarity and Justification** – Is the explanation clear and the reasoning well justified?
 - y_6 : **Hallucinations** – Does the output avoid fabricated or irrelevant information?
- $y_{\text{text}} \in \mathbb{T}$ is free-form natural language feedback (e.g., suggestions or rationale),
- $y_{\text{skip}} \in \{0, 1\}$ is a binary flag indicating whether evaluation was skipped due to missing or invalid input.

To quantify agent effectiveness for scenario evaluations, we employ the Pass^k metric. In contrast to the more widely used $\text{Pass}@k$ —which measures the likelihood that at least one of k independent attempts is successful— Pass^k estimates the probability that an agent succeeds on *all* k attempts. This more stringent criterion better reflects the reliability requirements of industrial applications, where retrying failed attempts may be infeasible and consistent behavior is critical for production systems [13]. In our benchmark, we report Pass^1 by default, as agents are executed only once per task instance but evaluation agent is executed 5 times to extract out the above performance metrics. We have set the sampling temperature to zero while executing the AgentOpsAgent and 0.3 for executing the evaluation agent. All reported results in this work follow this configuration.

5.1 AssetOpsBench Leaderboard

We conducted a series of benchmark experiments to evaluate a diverse set of language models, including closed-source models (e.g., gpt-4.1), frontier open-source models (e.g., llama-4-maverick, llama-4-scout, mistral-large, llama-3-405b), and medium-to-small open-source models (e.g., llama-3-70b, granite-3-8b). At present, we evaluated two different agentic strategies: *Tool-as-Agent* and *Plan-and-Execute*.

Tools-As-Agents Result. Figure 4 show that gpt-4.1 leads across nearly all metrics. llama-4-maverick also performs competitively, particularly in result verification (60%) and clarity (78%), with a low hallucination rate (11%). In contrast, smaller models such as granite-3-8b and llama-3-3-70b underperform across most dimensions. The comparatively lower baseline of smaller models highlights the potential of targeted fine-tuning approaches—such as those adopted in LAM framework—to significantly enhance their capabilities. Our default approach is Tool-as-Agent.

Plan-and-Execute Result. Figure 5 shows that mistral-large leads overall, achieving the highest scores in task completion (46.5%), action sequencing (58.1%), and competitive performance across

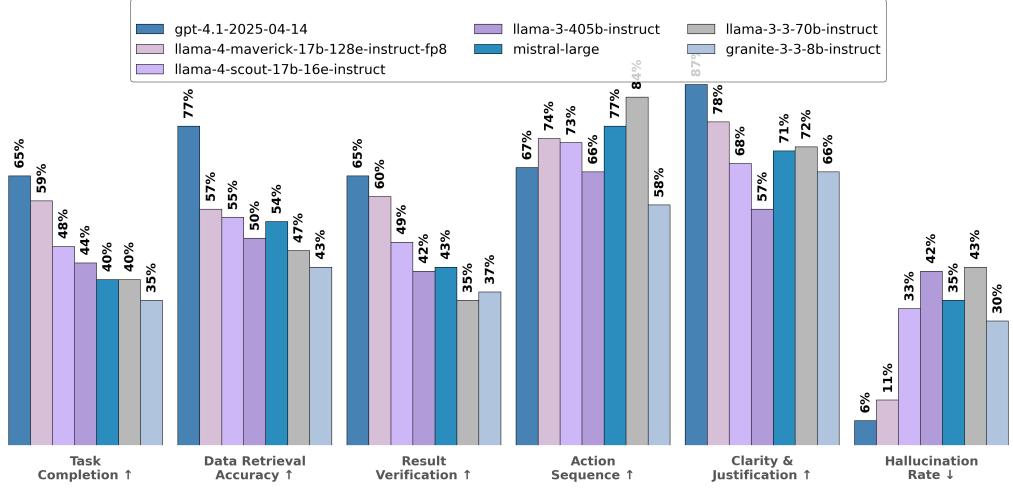


Figure 4: AssetOpsBench Leaderboard: Model Performance for **Agent-As-Tool** Approach

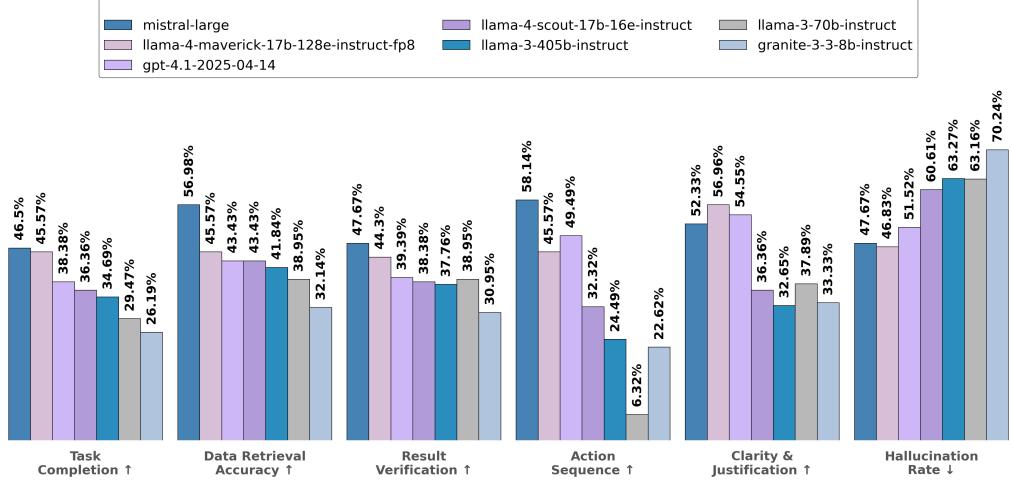


Figure 5: AssetOpsBench Leaderboard: Model Performance for **Plan-Execute** Approach

other dimensions. `llama-4-maverick` demonstrates balanced performance, particularly in clarity and justification (57%) and result verification (44%), while maintaining a moderate hallucination rate (47%). In contrast, models like `granite-3-8b` and `llama-3-70b` show lower scores across most metrics, especially in action sequence planning and factual consistency, with hallucination rates exceeding 63%. Interestingly, `gpt-4.1` achieves consistent mid-range performance across all axes, suggesting reliability but not leadership. These results underscore the challenges of long-horizon reasoning and sequencing in plan-and-execute settings, where even frontier models exhibit significant room for improvement. Additional observation about run-time is included in Appendix F.1.

Human Validation. To assess the reliability of using LLMs as automatic evaluators for benchmarking tasks, we compare model-generated judgments against human annotations on a sample of 40 tasks. Each task is evaluated along six dimensions by four domain experts, all operating under the same information constraints as the LLMs. Among the candidate models, `llama-4-maverick` shows the strongest alignment with human annotations, achieving **75% accuracy** and a **Cohen's Kappa score of 0.55**, outperforming `gpt-4.1` (69% accuracy, 0.44 Kappa). Based on this high level of moderate agreement with expert judgments, we adopt `llama-4-maverick` as the LLM to be used for evaluation agent for our benchmark (see Appendix F.2).

Ablation Study. We performed ablation experiments using Tool-as-Agent method: (1) We injected 10 out-of-domain distractors (e.g., SREAgent, EchoAgent) into system and evaluated 99 single-agent scenarios. Surprisingly, model performance *improved* in the presence of distractors—enhancing task completion, accuracy, and reasoning scores—suggesting that distractors may trigger more deliberate reasoning or robust attention strategies in LLMs. (2) We removed all in-context examples and re-ran 65 single-agent tasks (IoT+FMSR+TSFM) for both the best-performing model (gpt-4.1) and the worst-performing model (granite-3-8b). Performance plummeted from 80% to 34% for gpt-4.1 and from 60% to 3% for granite-3-8b, indicating that in-context examples are critical for enabling ReAct-style agents to coordinate and reason effectively. Detail analysis is in Appendix F.4.

5.2 Failure Modes of AssetOpsAgent

Just as industrial assets are prone to failure, recent research has begun to systematically categorize failure modes of multi-agent systems [1]. **AssetOpsBench** extends this line of work by supporting continuous monitoring and proactive identification of failure modes in LLM-driven agents. Our analysis draws on **881 execution trajectories** generated by Agents-as-Tool approach. We adopted the paper recommendation to use gpt-4.1 to discover the distribution of 14 failure modes defined in the framework [1]. Figure 6 shows the **system design** leads to many failures. To allow for discovery beyond the existing taxonomy, we adjusted the system prompt to self-discover up to two **novel failure modes** per trace if present. This enabled the detection of *emergent and compound failure behaviors* that are not fully captured by fixed taxonomies.

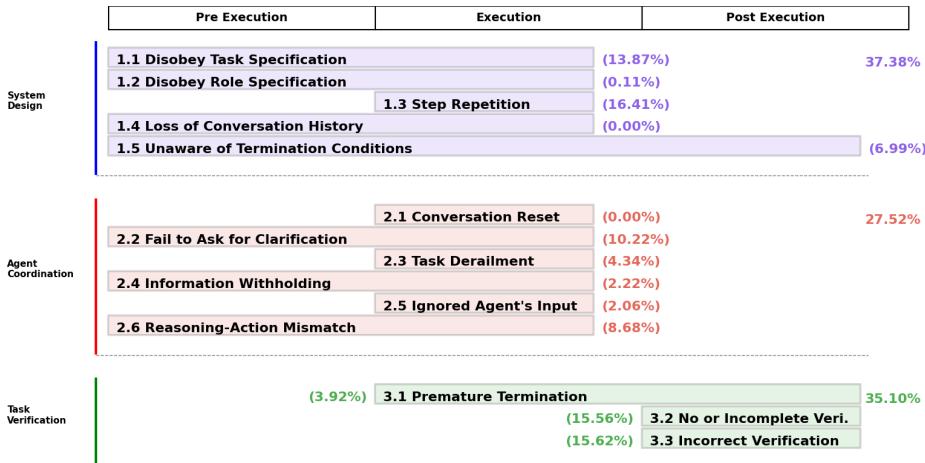


Figure 6: Distribution of the 14 failure modes on AssetOpsBench

Among the **881** trajectories analyzed, **185** included one novel failure mode beyond the current taxonomy, while **164** exhibited two distinct emergent issues. This reveals the need for extensible evaluation frameworks to capture the nuanced behaviors of real-world LLM-based agents. Frequently observed emergent failures include: **Overstatement of Task Completion** (122 cases, 23.8%); **Extraneous or Ambiguous Output Formatting** (110 cases, 21.4%); and **Ineffective Error Recovery** (160 cases). These observations underscore the importance of adaptive taxonomies that evolve alongside model behaviors. Appendix F.5 provides an algorithmic procedure for new failure mode discovery.

6 Limitations and Future Work

This paper introduces a formalized framework for AI agents for Industrial Assets, encompassing a comprehensive taxonomy, over 140 diverse scenarios derived from multi-source data, and a standardized evaluation methodology. The Tools-As-Agent paradigm offers a promising approach for orchestrating multi-agent interactions. However, our current setup assumes that API access to the environment is cost-free and unconstrained. In future work, we plan to introduce realistic environment constraints—such as compute limitations and API usage costs—to better reflect industrial settings and improve the robustness and efficiency of agent behavior.

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A Agents Definition

This appendix provides a detailed exposition of the content introduced in Section 3. In particular, we focus on the mathematical formulation of the agent architecture, followed by a brief overview of the proposed framework. The goal is to formalize the agent’s operational components and offer foundational context for readers interested in the underlying design principles.

A.1 Agent-Oriented Task Automation Problem - AOP

We formalize the Agent-Oriented Problem (AOP) as a tuple:

$$\text{AOP} = \langle \mathcal{A}, \mathcal{T}, \Pi, M, O \rangle$$

where each component defines a core capability of a modular, agent-based reasoning and action system:

- $\mathcal{A} = \{A_1, A_2, \dots, A_n\}$ denotes the set of available agents. Each agent A_i is characterized by its reasoning capabilities, task specialization, internal memory, and communication interfaces, enabling autonomous or cooperative execution of assigned subtasks.
- $\mathcal{T} = \{\tau_1, \tau_2, \dots, \tau_k\}$ is the set of tasks. Each task τ is described by a triple $\langle g, \mathcal{M}, C \rangle$, where g denotes the task goal (e.g., fault detection or maintenance planning), \mathcal{M} specifies the required input modalities (e.g., time-series telemetry, FMEA documents, structured metadata), and C captures any domain-specific or operational constraints (e.g., time windows, asset type, or safety requirements).
- Π is the hierarchical plan space. A plan $\pi \in \Pi$ is an ordered sequence of task-agent assignments:

$$\pi = [\langle \tau_1, A_i \rangle, \langle \tau_2, A_j \rangle, \dots]$$

where each subtask is delegated to an appropriate agent for execution, potentially with dependencies among steps.

- M denotes the memory system, consisting of both agent-local and shared global components. It is modeled as a dynamic key-value store $M = \{(k_i, v_i)\}_{i=1}^m$, supporting context persistence, lookup, and updates throughout the planning and execution process.
- O represents the output space. Each output $o \in O$ is the structured or unstructured result of executing a plan. Outputs may include diagnostics, action recommendations, summaries, or control triggers, depending on the task and domain.

A.2 Framework Introduction

AssetOpsBench uses the ReAct framework [29] in an end-to-end agent design that integrates a Review Agent to verify the final answer. Figure 7 illustrates the full architecture.

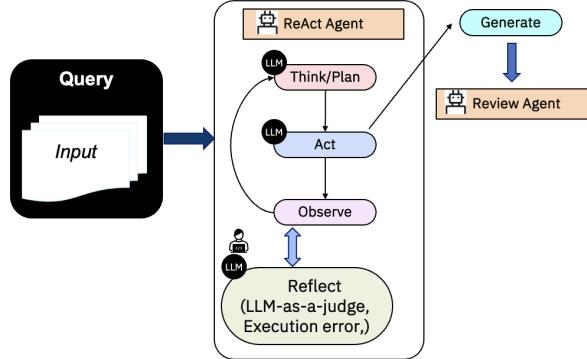


Figure 7: ReAct used to build individual agent

The ReAct agent executes a **Think-Act-Observe** loop, solving tasks iteratively while detecting and recovering from repetitive or ineffective actions. The Review agent validates whether the ReAct agent has successfully completed the task, ensuring output quality. Subsequent sections present the architecture in detail, highlighting the distinction between two architectural paradigms—**Agents-As-Tool** (See Section A.3) and **Plan-Execute** (See Section A.4).

A.3 Agent(s)-As-Tools/Tool-As-Agents

For the **Agents-As-Tools** paradigm as shown in Figure 8, we implemented the following components:

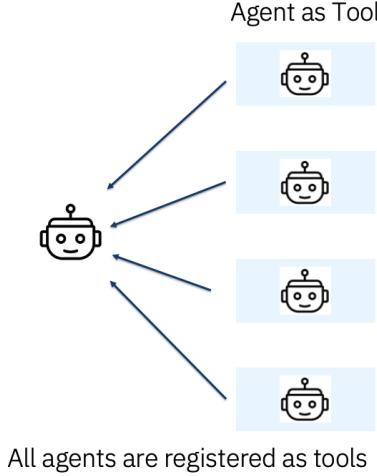


Figure 8: Agents-As-Tool

- A standard ReAct (Think–Act–Observe) agent loop using open source framework. In the initial setup, the *number of reflections* was set to one—effectively disabling reflection. We have extended version of ReActXen, and in future, we will conduct experiments to enable multi-step reflection within ReActXen.
- A curated list of tools, the majority of which are stub interfaces that delegate functionality to specialized sub-agents. The only standalone utility tool in this set was the `JSONReader`, which reads a JSON object from a file and returns its contents as the tool’s direct response.

The sub-agent stubs were intentionally designed to be minimal. Each stub accepted a single input parameter—a string called "request"—and returned a structured JSON output. The output JSON object included the following fields:

- `answer` – the primary answer returned by the sub-agent, represented as a plain string.
- `review` – a nested JSON object capturing a review of the response, typically including fields such as `status`, `reasoning`, and `suggestions`.
- `summary` – a brief description of the JSON object’s structure and semantics, useful for interpretability or chaining with downstream tools.

The ReAct agent was initialized with a standard prompt that includes:

- **Examples for In-Context Learning** – A small number of sample interactions for each sub-agent were provided to guide behavior. These examples followed the standard ReAct format of Think–Act–Observe, illustrating how to invoke tools and interpret their responses. A representative example is shown below:
- **Tool Demonstrations** – These sample calls were concatenated to form a comprehensive set of demonstrations for all tools available to the agent, effectively seeding it with usage patterns.

Listing 2: Example ReAct Prompt for IoTAgent

```

Question: download asset history for CU02004 at SiteX
from 2016-07-14T20:30:00-04:00 to 2016-07-14T23:30:00-04:00
for "CHILLED WATER LEAVING TEMP" and
"CHILLED WATER RETURN TEMP"

Action 1: IoTAgent
Action Input 1: request=download asset history for CU02004
at SiteX from 2016-07-14T20:30:00-04:00 to
2016-07-14T23:30:00-04:00 for "CHILLED WATER LEAVING TEMP"
and "CHILLED WATER RETURN TEMP"

Observation 1: {
  "site_name": "SiteX",
  "assetnum": "CU02004",
  "total_observations": 25,
  "start": "2025-03-26T00:00:00.000000+00:00",
  "final": "2025-04-02T00:00:00.000000+00:00",
  "file_path": "/var/folders/fz/.../cbmdir/c328516a-643f-40e6
    ↪ -8701-e875b1985c38.json",
  "message": "found 25 observations. file_path contains a JSON
    ↪ array of Observation data"
}

```

The sample calls for all the tools are concatenated to form the examples.

- question - the question input to ReAct
- tool names - the list of sub-agent tool names (plus JSONReader)
- tool descriptions - descriptions of the sub-agents

Execution Framework. The ReAct engine is reinitialized for each question and executed until either (a) successful completion—as determined by the Review component using an LLM-as-judge—or (b) a maximum of ten iterations. The framework iterates through a list of models (e.g., `mistralai/mistral-large`) and a corresponding list of utterances to execute for each model. The system supports retries for failed executions. After each ReAct run, the complete trajectory and associated evaluation metrics are stored. The recorded metrics include:

- **Question:** the input query being processed
- **Total execution time:** duration of the entire ReAct loop
- **Number of ReAct steps:** count of action-observation cycles
- **Review status:** success or failure determined by the LLM-based reviewer

A.4 Plan-and-Execute

Plan-and-Execute. *Plan-and-Execute* is a widely used architectural paradigm for multi-agent systems. Figure 9 depicts the implementation adopted in our work. The process initiates when a user submits a query, which is first processed by the **Planner**. The Planner decomposes the query into discrete, executable tasks. These tasks are then vetted by a **Reviewer** component to ensure quality, completeness, and relevance. Upon approval, the **Orchestrator** assigns the tasks to the most appropriate agents. Each agent independently executes its assigned task and returns a structured response. These responses are then aggregated by the **Summarization** module, which synthesizes them into a coherent final output that is returned to the user. This architecture supports modularity, robustness, and interpretability across the task lifecycle.

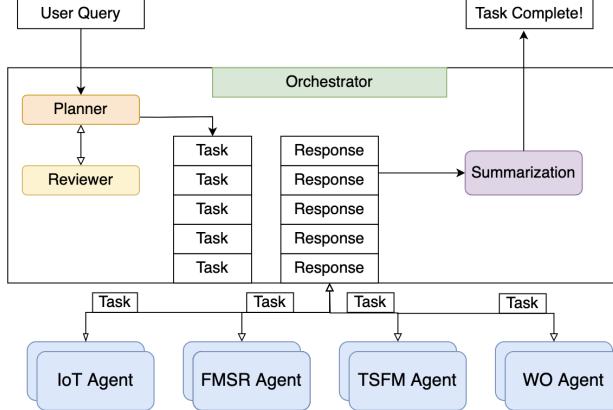


Figure 9: Plan-Execute Multi-Agent System

A.5 Example Demo

In the following Figures 10-12, we provide a few images to showcase working of Agents-As-Tool approach for a single end-to-end utterance.

```

Agent is Enabled with Reflexion
Task Execution Status (Finished): False
-----
Scratch Pad Content - At the Start of Running Agent
*****
I am ReActXen Agent with ReAct
Input Question: find anomalies in the chiller 6 return Temperature (POKMAIN) in the first week of 2016
Debug Info (Step 1):
{
  "thought": "I need to request the chiller 6 return temperature data for the first week of 2016 from IoTAgent",
  "llm_output": " I need to request the chiller 6 return temperature data for the first week of 2016 from IoTAgent
t\nAction"
}
Thought 1: I need to request the chiller 6 return temperature data for the first week of 2016 from IoTAgent
Debug Info (Step 1):

```

Figure 10: Execution is Initiated with an input query.

```

Action 3: Finish
Action Input 3: The anomaly detection results of 'Chiller 6 Return Temperature' using data in /var/folders/fz/1lh7gpv96rv5lg6m_d6bk0gc000gn/T/cbmdir/2e2eea99-946c-4a30-a688-8ddfa479ab62.json are stored in file ../output/tsad_output//tsad_conformal.csv Final Answer: The anomaly detection results of 'Chiller 6 Return Temperature' using data in /var/folders/fz/1lh7gpv96rv5lg6m_d6bk0gc000gn/T/cbmdir/2e2eea99-946c-4a30-a688-8ddfa479ab62.json are stored in file ../output/tsad_output//tsad_conformal.csv Question
Process is completed now
Task Execution Status (Finished): True
Review Agent Feedback: {'status': 'Accomplished', 'reasoning': "The agent successfully executed the task by performing time series anomaly detection on 'Chiller 6 Return Temperature' using the data from the specified file. The agent used the tsfm_integrated_tsad tool with the correct dataset path, timestamp column, and target columns. The agent then stored the results in the specified output file. The response provides a clear and accurate description of the task completion, including the location of the output file.", 'suggestions': 'None.'}
run minutes = 2.1432575666666667

```

Figure 11: The Final step of the execution

B Detailed AssetOps Hierarchy

This appendix presents the structured task taxonomy used in AssetOpsBench, which organizes benchmark scenarios based on key stages in the industrial asset lifecycle. The taxonomy is designed to support the creation of realistic, diverse, and role-specific evaluation tasks for intelligent agents operating in complex environments, as shown in Figure 13 for the tasks related to the industrial asset management.

To illustrate how the structured task taxonomy guides agent development and evaluation, we highlight four representative agents: the IoT Agent, the FMSR Agent (Failure Mode Sensor Relations Agent), TSFM (Time Series Foundation Model) Agent, and the WO Agent (Work Order Agent).

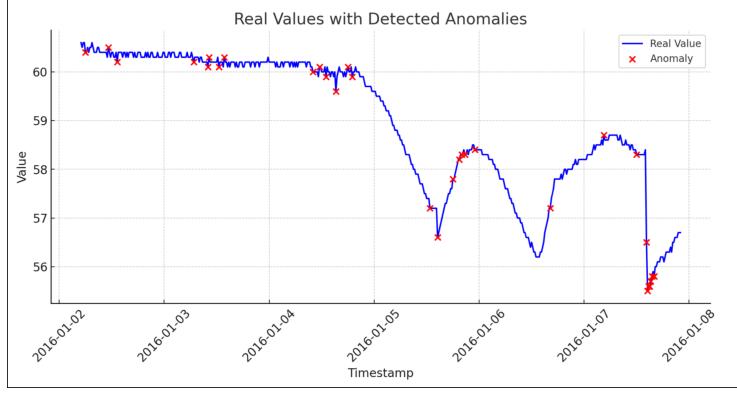


Figure 12: Anomaly Detection : Final Output



Figure 13: Representative Routine tasks in Asset Lifecycle Management.

Among these, two agents—FMSR Agent and WO Agent—are particularly useful for their domain specialization and integration depth within AssetOpsBench. Appendix B.2 presents the rationale for FMSR Agent, emphasizing its role in bridging raw telemetry with diagnostic reasoning through sensor–failure mapping. Appendix B.4 focuses on the WO Agent, which operationalizes maintenance planning and historical analysis by retrieving, filtering, and correlating work order records with asset conditions. Together, these examples demonstrate how high-level task categories—such as failure mode alignment, anomaly response, and intervention prioritization—are translated into grounded, data-driven agent behaviors. This alignment reinforces AssetOpsBench’s emphasis on transparency, domain specialization, and end-to-end task automation.

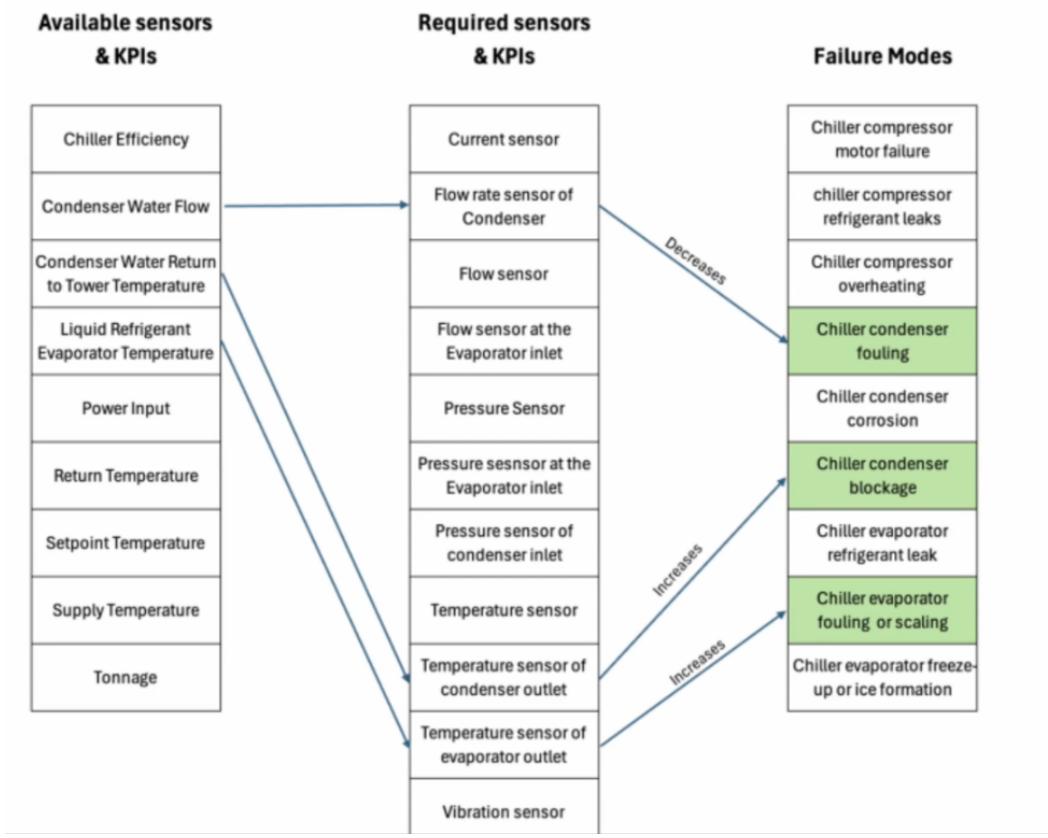


Figure 14: Mapping Example internally used by FMSR Agent

B.1 Rationale for IoT Agent over Application

The IoT Agent plays a foundational role in supporting **Asset Configuration** tasks within the AssetOps framework, as illustrated in Figure 13. It enables structured access to real-time and historical telemetry data, asset metadata, and site configurations. Specifically, it allows users to query available IoT-enabled sites, list all assets within a given site (e.g., MAIN facility), and retrieve detailed metadata for specific assets such as chillers and air handling units (AHUs). Additionally, it provides access to time-series sensor data—such as power input, temperature, flow rate, and system tonnage—across customizable time windows. These data queries form the backbone for monitoring tasks, model inputs, and analytics performed by downstream agents like TSFM Agent and WO Agent.

Although the IoT Agent does not perform anomaly detection or failure analysis directly, it is a critical enabler by delivering high-fidelity, time-aligned telemetry required for advanced applications (such as those using TSFM Agent). For example, users can retrieve the tonnage data for Chiller 6 during a specific week, download metadata for Chiller 9, or access sensor values recorded during a known operational event. These capabilities align with the early-phase needs of asset lifecycle management—specifically selecting data sources and configuring metrics of interest—ensuring all downstream decision-making is grounded in accurate, context-rich operational data. The agent's flexible query interface and knowledge and data retrieval support allow it to seamlessly integrate into automated pipelines for asset monitoring, diagnostics, and performance tracking.

B.2 Rationale for FMSR Agent over Application

The sensor–failure alignment generation (See Figure 14) is a critical component of the **AssetOps-Bench** benchmark, serving multiple roles in both dataset understanding and intelligent system design. Its inclusion is motivated by the following key factors:

- Bridging Raw Data and Diagnostic Insight:** The table explicitly maps sensor variables to relevant failure modes, establishing a direct link between low-level telemetry and high-level maintenance reasoning. This supports tasks such as fault detection, root cause analysis, and feature selection for learning-based systems.
- Alignment with FMEA Methodology:** By structuring failure explanations according to the principles of Failure Modes and Effects Analysis (FMEA), the table offers a formalized, interpretable view of asset health. Each sensor's diagnostic role is contextualized through failure causes, effects, and detection implications.
- Supporting Explainability and Safety:** In industrial environments, operational decisions require transparency. The alignment table enhances system explainability by clarifying why a given signal is relevant, how it relates to equipment health, and what operational risks it may indicate.
- Improving Dataset Transparency:** The AssetOpsBench dataset includes a wide range of sensors across multiple devices. This table functions as a documentation layer that improves usability, reproducibility, and understanding for researchers and practitioners engaging with the benchmark.
- Guiding Model and Rule Development:** Whether designing rule-based systems, hybrid AI architectures, or physics-informed machine learning models, a well-defined mapping of sensors to failure mechanisms is foundational. It informs the construction of robust detection logic and contributes to generalizable reasoning strategies.

In sum, the sensor–failure alignment table plays a central role in transforming raw operational telemetry into structured, actionable insight. It provides the semantic grounding necessary for developing interpretable, reliable, and effective AI agents for real-world industrial maintenance tasks. Table 3 provides an extensive example for sensor-failure mode relation for a chiller system.

Table 3: Sensor Interpretation and Failure Mode Relevance in Chiller Systems - Illustrative

Sensor	Explanation	Impact on Chiller Health / Failure Mode Relevance
Condenser Leaving Temp	Temperature of water leaving the condenser	Indicates heat rejection efficiency; abnormal readings may signal fouling or reduced flow — potential <i>heat exchange failure</i> .
VFD Output Voltage	Voltage output from Variable Frequency Drive	Instability may affect fan/compressor operation — linked to <i>electrical drive failure</i> or <i>load imbalance</i> .
CHWSTSP in Free Mode	Chilled water setpoint during free cooling mode	Misconfiguration can lead to energy inefficiency — related to <i>control logic failure</i> .
Cycling Code	Indicates compressor cycling state	Frequent cycles may indicate <i>load mismatch</i> , <i>sensor error</i> , or <i>compressor stress</i> .
Ready Status	Indicates if chiller is in a ready state	Persistent unavailability may reflect <i>control override</i> , <i>interlock failure</i> , or <i>alarm lockout</i> .
Manual Start/Stop	Overrides for manual operation	May cause <i>unscheduled runtime</i> or <i>safety override</i> conditions.
Chilled Water Leaving Temp	Temperature leaving evaporator	Deviation may suggest <i>capacity loss</i> or <i>improper load conditions</i> .
Condenser Flow	Water flow through condenser loop	Low flow may cause <i>high pressure shutdown</i> or <i>heat rejection failure</i> .
VFD Input Power	Power input to VFD	Spikes may indicate <i>motor inefficiency</i> , <i>overload</i> , or <i>harmonic distortion</i> .
CNW Flow Hi Alarm SP	High flow setpoint for condenser loop	May indicate <i>bypass valve issues</i> or <i>over-pumping</i> .
Watt/Ton	Cooling efficiency metric	Rising ratio suggests <i>energy inefficiency</i> or <i>component degradation</i> .

Sensor	Explanation	Impact on Chiller Health / Failure Mode Relevance
Chilled Water Flow	Water flow through evaporator	May point to <i>pump failure, valve issues, or airlocks</i> .
Motor Run Status	Compressor motor operational state	Discrepancies could signal <i>false starts, sensor error, or runtime misreporting</i> .
Vibration Point #1 SP	Vibration sensor setpoint (location #1)	May indicate <i>bearing failure, imbalance, or mechanical looseness</i> .
CHW Valve Position	Position of chilled water valve	Out-of-range position may imply <i>valve actuator fault or control misbehavior</i> .
CHW Differential Pressure (D/P)	Pressure drop across chilled water loop	Suggests <i>clogging, filter fouling, or flow resistance</i> .
CHW Flow Hi Alarm SP	Alarm setpoint for high CHW flow	Triggered by <i>pump overspeed, valve overshoot, or control issues</i> .
Condenser Return Temp	Water temperature returning to the condenser	Important for <i>thermal load calculation and monitoring efficiency</i> .
Average Amps	Average motor current	High current may indicate <i>overload, bearing drag, or electrical faults</i> .
CHW Valve Close Control	Control signal to close CHW valve	Improper function may cause <i>flow issues or unmet loads</i> .
CNW Differential Pressure (D/P)	Pressure drop in condenser loop	Indicates <i>scaling, fouling, or pump degradation</i> .
VFD Internal Ambient Temp	Internal temperature of VFD	High temps may trigger <i>thermal trips or shorten VFD lifespan</i> .
Freon Temp	Refrigerant temperature	Abnormal values may suggest <i>charge issues, expansion valve faults, or heat exchange failure</i> .
Compressor Oil Sump Temp	Oil sump temperature	High temperature may signal <i>bearing wear or insufficient cooling</i> .
Chilled Water Return Temp	Return water temp to evaporator	Used for <i>cooling load and delta-T analysis</i> .
Motor Run Status RPT	Reported motor run confirmation	Mismatch suggests <i>sensor/control error</i> .
VFD Inverter Link Current	Current through VFD inverter link	High current may indicate <i>overload or VFD stress</i> .
CHWSTSP in Part Mode	Setpoint in partial load mode	Improper configuration can cause <i>energy waste or load mismatch</i> .
VFD Phase A/B/C Current	Phase currents from VFD	Used to detect <i>imbalances, shorts, or phase loss</i> .
VFD Converter Heat Sink Temp	VFD heat sink temperature	Elevated temps reduce <i>component life</i> and can cause <i>failure</i> .
Compressor Oil Pressure	Oil pressure in compressor	Low pressure risks <i>lubrication failure and component damage</i> .
Failure (status flag)	Direct failure indicator	Used as ground truth label for fault evaluation.
VFD Setpoint	Speed or torque command	Affects <i>energy usage, response time, and cooling capacity</i> .
CHW Flow High Alarm	High flow warning flag	May indicate <i>system control faults or oversized flow components</i> .
VFD DC Bus Voltage	DC voltage level inside VFD	Instability can reflect <i>power quality issues</i> .

Sensor	Explanation			Impact on Chiller Health / Failure Mode Relevance
CNW Alarm	Flow	High	High condenser water flow warning	May reflect valve misposition or energy inefficiency.
CNW Alarm SP	Flow	Low	Low flow alarm threshold	Indicates risk of overheating or shutdown due to poor heat rejection.
Warning Code			Non-critical warning status	Helpful for early diagnostics or trend detection.
Vibration #2/#3 SP	Points		Additional vibration set-points	Detect imbalance, wear, or mechanical degradation.

B.3 Rationale for TSFM Agent over Application

The TSFM Agent is purpose-built to support critical tasks within the **AssetOps** workflow, as outlined in Figure 2. Within **Model Selection and Analysis**, TSFM Agent enables forecasting of key performance indicators (KPIs) using lightweight, pre-trained foundation models such as TTM¹. Its adaptive anomaly detection framework, based on post-hoc conformal prediction, supports calibrated and interpretable anomaly scores, providing high utility for both **Monitoring and Execution** and **Maintenance and Response**.

Specifically, the TSFM Agent can execute and refine models, classify anomalies based on historical deviations, and support operational guardrails by simulating expected trends under normal conditions. In downstream applications, the agent’s outputs can be used to summarize overall system health by tracking the frequency of anomalies across selected KPIs. These anomalies serve as a foundation for maintenance recommendations, enabling preventive and reactive work order generation. TSFM Agent facilitates real-time, data-driven decision-making throughout the asset lifecycle.

B.4 Rationale for WO Agent over Application

The WO Agent, a code-based ReAct, in **AssetOpsBench** is designed to enable intelligent interaction with structured and unstructured maintenance records through a modular data model. It operates over a set of *Business Objects* (BOs) that represent work orders, alerts, anomalies, failure codes, and asset metadata. These BOs are categorized into five functional groups that collectively support the WO Agent’s decision-making capabilities.

To reason over these BOs, the WO Agent is equipped with a collection of analytic functions that allow it to retrieve, interpret, and act upon historical and real-time data. The agent’s capabilities are structured as follows:

1. **Historical Reasoning via Content Objects and Knowledge Extraction:** The WO Agent accesses raw maintenance data such as *WorkOrders*, *Events*, including Work orders, alerts, and anomaly Events. Knowledge extraction functions enable the agent to retrieve and filter this data by date, asset, and work order type, allowing targeted analysis and retrospective diagnostics.
2. **Standardized Interpretation with Meta/Profile Objects:** BOs like *ISO Failure Code*, *AlertRule*, and *Equipment* provide structured classification schemes. These allow the agent to categorize failures, apply semantic filters, and maintain compatibility with domain conventions—critical for aligning alerts and anomalies with actionable categories.
3. **Temporal and Causal Reasoning via Statistical Functions:** Leveraging relationship BOs such as *Alert-Rule Mapping* and *Anomaly Mapping*, the WO Agent applies statistical functions (e.g., Allen’s Interval Algebra) to detect temporal patterns—such as when alerts consistently precede failures. It also detects repeated work order cycles, helping align maintenance with actual degradation patterns instead of fixed schedules.
4. **Predictive and Prescriptive Intelligence through Decision Support Functions:** Using the *WorkOrderRecommendation* BO, the agent forecasts future work orders, recommends

¹<https://huggingface.co/ibm-granite/granite-timeseries-ttm-r1>

maintenance based on alerts or KPI anomalies, and identifies opportunities for bundling related tasks. These decision support functions enable proactive scheduling and optimize resource use across the asset lifecycle.

- 5. Persona-Aligned Interaction and Query Resolution:** The WO Agent interfaces naturally with domain personas. Maintenance engineers can explore past interventions for a given failure, while planners can query upcoming work order demands or seek opportunities to consolidate tasks. These capabilities are backed by modular functions that support flexible querying and planning logic.

In summary, the WO Agent is a hybrid reasoning and decision-support agent built atop structured business objects and analytic functions. It connects historical insight with predictive planning, enabling lifecycle-aware maintenance interventions grounded in transparent, data-driven logic.

Table 4: WO Agent Summary of Business Objects, Source, Role, and Number of Records

Business Object	Source	Role	Count
Content Objects			
WorkOrder	Work Order Manager	Tracks scheduled and unscheduled maintenance tasks, categorized as preventive or corrective.	4392
Event	Aggregated by Authors	Consolidates event logs for tracking and decision-making.	6929
Alert Events	IoT Repository	Logs real-time alerts triggered by IoT sensors based on predefined conditions.	1995
Anomaly Events	ML Generated	Detects KPI deviations using machine learning for predictive maintenance.	542
Meta/Profile Objects			
ISO Failure Code	Developed by Authors	Standardizes failure classification for structured maintenance analysis.	137
ISO Primary Failure Code	Developed by Authors	Defines primary failure categories and links related secondary codes.	68
AlertRule	SME Provided	Specifies conditions for triggering alerts based on system behaviors.	77
Equipment	SME Provided	Represents industrial assets, including status and specifications.	22
Relationship Causality Objects			
Alert-Rule Mapping	Relationship Causality	Links alert rules to failure codes for automated diagnostics.	46
Anomaly Mapping	Relationship Causality	Associates anomalies with failure codes for predictive insights.	12
Recommendation Objects			
WorkOrder Recommendation	Recommendation	Suggests maintenance actions based on historical patterns.	N/A

Note: The design and structure of the business objects and corresponding analysis in this section are valid for other industrial asset types, such as standby generators.

C Scenario Creation Principles

The scenarios in **AssetOpsBench** are crafted to evaluate a broad spectrum of capabilities expected from autonomous agents in industrial settings. Each scenario is designed to challenge specific dimensions of reasoning, tool use, data interpretation, communication, and decision-making, as outlined below:

- **Reasoning and Tool Use:** Assesses domain-specific reasoning such as time and schema operations, appropriate tool invocation, and structured command generation. Common failure modes include premature halts or misuse of tools.
- **Data Handling and Forecasting:** Evaluates the agent’s ability to interpret telemetry, detect anomalies, and configure appropriate forecasting or anomaly detection models. Tasks often require translating domain knowledge into ML configuration steps (e.g., model selection, fine-tuning).
- **Agent Communication and Coordination:** Tests multi-agent workflows involving targeted question-asking, summarization, and collaborative decision-making. Scenarios mimic how agents may delegate or escalate tasks in real settings.
- **Workflow Orchestration and Decision-Making:** Measures the agent’s ability to plan and manage dependent subtasks, reason under uncertainty, and terminate appropriately when faced with ambiguity or missing data.

C.1 Examples

We include two examples (Table 5 and Table 6) that showcase distinct behaviors of agent outputs. Readers can observe that the *characteristic form* varies even for problems that appear similar on the surface.

Table 5: Example Knowledge Query: Energy Prediction for Chiller 9

Field	Description
ID	507
Type	Knowledge Query
Text	What is the predicted energy consumption for Chiller 9 in the week of 2020-04-27 based on data from the MAIN site?
Characteristic Form	The expected response should confirm the successful execution of all required actions, ensuring that the correct asset (Chiller 9), location (MAIN), and time range (week of 2020-04-27) were used for data retrieval and analysis. It should specify that the agent identified the sensor name (<i>power input sensor</i>) and retrieved the historical energy consumption data for Chiller 9 during the specified time period. The response must also explain that the agent attempted to analyze the data for energy consumption prediction, but was unable to do so due to insufficient data, as the power input for Chiller 9 was consistently 0.0 from 2020-04-20 to 2020-04-25, indicating that the chiller was not operating.

D Datasets for AssetOpsBench and Utilization by Agents

In this part, as extension of Section 4.1, we will zoom into the datasets utilized by the various agents of **AssetOpsBench** (More details of the roles of the agents in the asset lifetime management can be found at Appendix B).

D.1 Sensor Telemetry Dataset for IoT Agent and TSFM Agent

Both IoT Agent and TSFM Agent (Figure 2) leverage the **Sensor Telemetry Dataset**, which comprises sensor telemetry collected from Building Management Systems (BMS) and the SkySpark analytics platform. This dataset captures fifteen-minute interval operational data from industrial HVAC systems, specifically a fleet of chillers. Each chiller unit (e.g., Chiller 4, Chiller 14) is instrumented with a standardized suite of physical sensors that monitor key operational parameters in real-time.

A representative subset of these sensors is summarized in Table 7. These sensors record various kinematic, dynamic, thermodynamic, electrical, and operational metrics essential to assessing the performance and health of chiller systems. Measurements include water and refrigerant temperatures,

Table 6: Example Knowledge Query: Predicting Energy Usage for Chiller 9

Field	Description
ID	511
Type	Knowledge Query
Text	Can you predict Chiller 9's energy usage for next week based on data from the week of 2020-04-27 at MAIN?
Characteristic Form	The expected response should confirm the successful execution of all required actions, ensuring that the correct asset (Chiller 9) and location (MAIN site) were used for data retrieval and analysis. It should specify that the agent first identified the sensors for Chiller 9, then selected the <i>Chiller 9 Power Input</i> sensor, and successfully retrieved the energy usage data for the specified time period. The response should confirm that the agent provided the file path where the data is stored. Additionally, it should mention that although the agent initially encountered errors while analyzing the data and making predictions, it successfully corrected its mistakes and finetuned a Time Series Forecasting model using the provided data. The agent should have used the finetuned model to generate predictions for the next week, with the results being stored in the specified file.

power consumption, cooling capacity (tonnage), flow rates, and system setpoints. Additionally, computed metrics such as chiller efficiency and load percentage serve as valuable real-time indicators of system performance.

Table 7: Representative Sensors in the **AssetOpsBench** Dataset

Sensor Name	Description
Chiller Return Temperature	Temperature of water returning to the chiller
Supply Temperature	Temperature of water exiting the chiller
Power Input	Electrical power consumption
Tonnage	Heat extraction rate (cooling capacity)
Condenser Water Supply to Chiller Temperature	Temperature of water supplied to the condenser
Chiller Efficiency	Instantaneous performance metric
Chiller % Loaded	Current load as a percentage of the maximum
Condenser Water Flow	Flow rate through the condenser
Liquid Refrigerant Evaporator Temperature	Temperature of refrigerant in the evaporator
Run Status	Binary indicator of whether the chiller is currently operating
Setpoint Temperature	Current setpoint for chiller operation

Each sensor stream is accompanied by rich metadata, including sensor type, measurement units, physical location, and structured device tags that define device associations. The dataset captures realistic operational variability, encompassing noise, missing data, and seasonal patterns. As such, it provides a robust foundation for developing and benchmarking models that require temporal reasoning, fault detection, and decision-making under uncertainty.

As illustration, Figure 15 presents layered time series subplots for key chiller sensors over a selected snapshot period in June 2020 for Chiller 6. Each subplot corresponds to one sensor variable, enabling a clear view of temporal dynamics and inter-variable behavior. This figure provides insight into the operational profile of a single chiller unit during real-world usage.

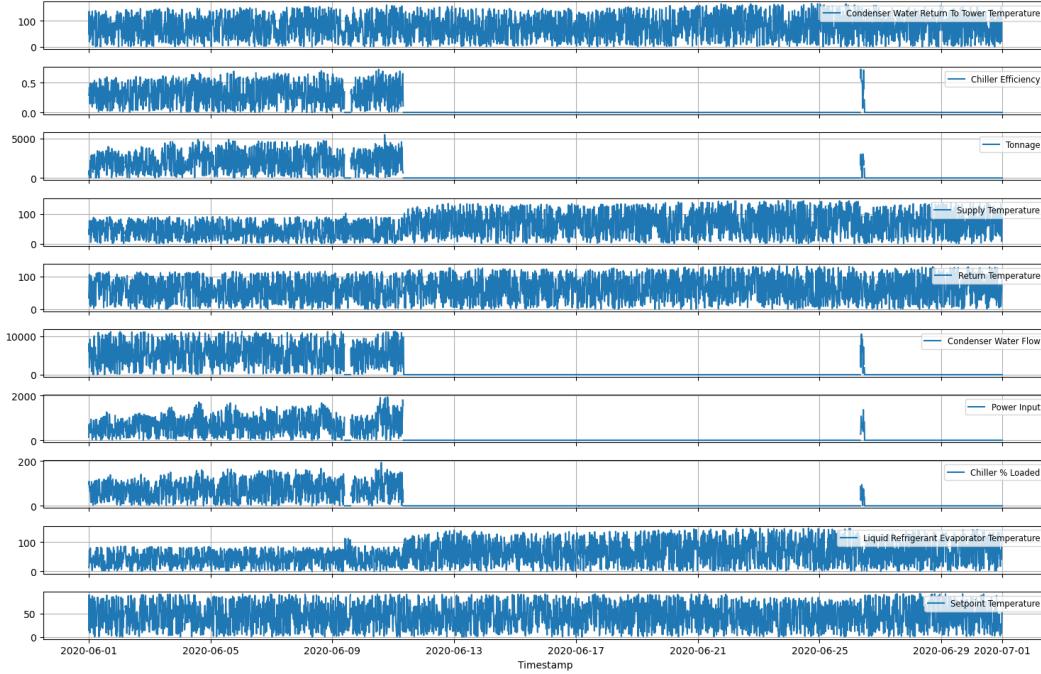


Figure 15: Snapshot of time series data from Chiller 6 for June 2020. Each subplot shows an individual sensor’s trend over time.

The IoT Agent interacts with this telemetry data through structured utterances. By leveraging the standardized data provided by **AssetOpsBench**, the agent enables detailed, query-driven access to operational information across HVAC assets such as chillers and air handling units (AHUs) at IoT-enabled sites like the MAIN facility. Through these utterances, users can request both real-time and historical data, retrieve metadata, and download sensor readings for specific timeframes. This functionality supports knowledge and data queries, facilitating asset-level diagnostics, performance monitoring, and intelligent decision-making, even in noisy or incomplete data.

On the other hand, the TSFM Agent operates on sensor telemetry data—either retrieved via the IoT Agent or accessed directly from the sensor repository—to perform advanced time series analysis across HVAC systems. It supports a range of analytical tasks, including multivariate forecasting, and time series anomaly detection. At its core, the agent utilizes pre-trained time-series foundation models, such as TTM variants (see footnote²). TTM (Tiny Time-series Mixture) is a lightweight, pre-trained time-series foundation model designed for efficient multivariate forecasting. For anomaly detection, the TSFM Agent applies a model-agnostic, post-hoc adaptive conformal method that requires no additional fine-tuning data, making it highly practical for real-world, resource-constrained deployments. By learning dynamic weighting strategies from prediction histories, it can detect distributional shifts and maintain calibrated, interpretable anomaly scores aligned with user-defined false alarm rates. Through structured utterances, users can invoke forecasting on specific variables (e.g., “Chiller 9 Condenser Water Flow”), fine-tune models with minimal data, or detect anomalies in historical trends—all with minimal configuration. This seamless integration of pre-trained models, adaptive analytics, and user-guided queries enables transparent, robust, and immediately deployable monitoring solutions tailored for critical industrial systems.

D.2 Failure Mode Datasets for FMSR Agent

The failure mode datasets in **AssetOpsBench** are modeled using the principles of *Failure Modes and Effects Analysis* (FMEA), a structured framework used in reliability engineering to identify failure risks, assess root causes and effects, and inform condition-based maintenance strategies. Each

²<https://huggingface.co/ibm-granite/granite-timeseries-ttm-r2>

failure is defined by its mode, degradation mechanism, detection opportunity, and operational impact, enabling structured reasoning for both rule-based diagnostics and machine learning.

Failures in the dataset are annotated at the asset and subsystem levels, with a primary focus on centrifugal chillers. These failures reflect realistic degradation pathways and operational stressors derived from field experience. Each record in the failure model includes:

- **Failure Location and Component:** The subsystem or part where failure occurs, such as *bearings, gearboxes, impellers, or lubrication systems*.
- **Degradation Mechanism:** The underlying physical process driving the failure, including *wear, erosion, oil degradation, vibration-induced fatigue, and misalignment*.
- **Degradation Influences:** External or internal stressors such as *run time, two-phase process fluid, personnel error, or shock loading*.
- **Functional Failure Mode:** The resulting operational defect, such as *decreased oil pressure, audible noise, low head pressure, or capacity loss*.
- **Detection Opportunities:** Observable precursors or symptoms, including sensor readings (e.g., oil sampling, vibration signals), condition-based alarms, or inspection results.
- **Repair Time and Criticality:** Estimated downtime and classification of failure risk, supporting cost-based prioritization and scheduling.
- **Preventive Task Type:** Associated maintenance activity, such as *oil analysis, vibration analysis, or visual inspection*, tagged with effectiveness ratings and intervention intervals.

For example, *bearing wear*—a recurring failure across chiller subsystems—may arise from lubrication failure, misalignment, or fluid shock loading. This degradation is detectable via a combination of oil analysis and vibration monitoring, with failure symptoms including increased vibration, reduced oil pressure, and audible anomalies. Similarly, impeller erosion is linked to aging and two-phase fluid exposure, typically presenting as reduced capacity and lower head pressure.

Each maintenance task in the dataset is mapped to its detection mechanism and action type (e.g., condition monitoring vs. corrective repair), along with documentation on task content and recommended frequency. These structured records not only support early fault detection and diagnostics but also facilitate benchmarking of intelligent agents’ reasoning over real-world degradation patterns and maintenance decisions.

Failures are temporally aligned with telemetry, enabling the study of degradation trajectories and pre-failure conditions. This integrated design makes the dataset suitable for supervised learning, causal inference, and evaluation of digital twins or predictive maintenance agents under realistic operating uncertainty.

To utilize the failure modes and their association with the sensors, we design FMSR (Failure Mode Sensor Relations) to interpret failure mode datasets within the **AssetOpsBench** framework, leveraging structured FMEA (Failure Modes and Effects Analysis) principles to link sensor telemetry with degradation mechanisms and operational failures. Using annotated failure records for assets such as centrifugal chillers, the FMSR Agent builds knowledge graphs and reasoning models that connect specific failure modes—like compressor overheating, evaporator fouling, or refrigerant valve failure—to their underlying causes and detectable symptoms. These failure modes are mapped to available sensor measurements (e.g., supply temperature, power input, vibration, flow rate) to identify observable precursors. For example, compressor overheating may be monitored through trends in power input, chiller efficiency, and evaporator temperature, while condenser fouling can manifest in abnormal return temperatures and flow rate deviations. Through structured utterances, users can query which failure modes are associated with specific sensors, which are critical for detecting a given failure, or even construct machine learning recipes for predictive modeling—such as anomaly models for chiller trips or excessive purging. The agent leverages this data to perform rule-based diagnostics, support causal analysis, and assist in condition-based maintenance planning. By aligning temporal sensor patterns with known failure signatures, the FMSR Agent enables explainable fault detection and root cause inference, ultimately enhancing reliability, maintainability, and transparency in HVAC operations.

Table 8: Work Order Event Schema Definition

Field Name	Type	Description
wo_id	String	Unique identifier for the work order. Example: "L247402"
wo_description	String	Description of the work being done. Example: "CHILLER COMP OIL ANALYSIS"
collection	String	Broad group or system the work relates to. Example: "compressor"
components	String	Specific part or component being serviced. Example: "compressor"
primary_code	String	Code representing the main type of work. Example: "MT010"
primary_code_desc.	String	Description of the primary work code. Example: "Oil Analysis"
secondary_code	String	Sub-code under the primary category. Example: "MT010b"
secondary_code_desc.	String	Description of the secondary code. Example: "Routine Oil Analysis"
equipment_id	String	Unique ID of the equipment. Example: "CU02013"
equipment_name	String	Human-readable name of the equipment. Example: "Chiller 13"
preventive	Boolean	Indicates if this is preventive maintenance. Example: TRUE
work_priority	Integer	Priority level of the work (e.g., 1–5). Example: 5
actual_finish	DateTime	Date and time when the work was completed. Example: "4/6/16 14:00"
duration	Duration	Total job time. Format: HH:MM. Example: "0:00"
actual_labor_hours	Duration	Actual labor time spent. Format: HH:MM. Example: "0:00"

Table 9: Alert Event Schema Definition

Field Name	Type	Description
equipment_id	String	Unique identifier for the equipment that triggered the alert. Example: "CWC04701"
equipment_name	String	Human-readable name of the equipment. Example: "Chiller 1"
rule_id	String	Identifier for the rule or condition that triggered the alert. Example: "RUL0021"
start_time	DateTime	Timestamp when the alert or event started. Example: "11/24/20 19:00"
end_time	DateTime	Timestamp when the alert or event ended. Example: "11/24/20 23:59"

D.3 Work Order Datasets for WO Agent

Table 4 provide the summary of datasets (as business objects) and the size for each dataset. Those work order datasets in **AssetOpsBench** provide a structured view of maintenance activity across industrial assets, encompassing both preventive and corrective interventions using work orders. Each

Table 10: Anomaly Event Schema Definition

Field Name	Type	Description
timestamp	DateTime	The date and time when the anomaly event was recorded. Example: "4/26/20 14:14"
KPI	String	The key performance indicator being monitored (e.g., "Cooling Load").
asset_name	String	The name of the asset or equipment being measured. Example: "chiller 9"
value	Numeric	The actual measured value of the KPI at the given timestamp. Example: 25978710
upper_bound	Numeric	The upper threshold for the KPI. Exceeding this may indicate an anomaly.
lower_bound	Numeric	The lower threshold for the KPI. Falling below this may indicate an anomaly.
anomaly_score	Float	A score indicating how likely the data point is an anomaly (typically 0 to 1).

Table 11: Mapping Table: KPI Anomalies to Failure Codes

Field Name	Type	Example	Description
kpi_name	String	Cooling Load	Name of the key performance indicator exhibiting anomaly.
anomaly_type	String	High	Indicates the direction or nature of the anomaly (e.g., High, Low, Spike).
category	String	Operational Failures	Broad class of the failure (e.g., Control System, Structural, External, Human).
primary_code	String	OP004	Primary failure code associated with the anomaly.
pri._code_des	String	Incorrect Cooling Zone Operation	Explanation of the primary failure code.
seco._code	String	OP004c	More specific sub-code refining the root cause.
seco._code_des	String	Improperly Controlled or Shut Off Zones	Description of the secondary failure code.

work order is associated with rich contextual data including equipment metadata, failure classification codes (e.g., ISO Failure Code, ISO Primary Failure Code), event logs, sensor-triggered alerts, and machine-generated anomalies. These records are linked temporally and causally, allowing agents to reason about asset history, detect recurring failure patterns, and recommend actions based on past interventions.

The group of datasets distinguishes between core content objects (e.g., WorkOrders, Alerts, Events, Anomalies), metadata profiles, and relational structures that map alerts and anomalies to failure codes.

The individual event tables — *work orders* (Table 8), *alert events* (Table 9), and *anomaly events* (Table 10) — capture different but complementary signals related to equipment condition and behavior. To enable integrated analysis and causal reasoning, these events are unified into a common *event table schema* (Table 12), allowing temporal alignment and cross-type relationship discovery between maintenance actions, system warnings, and performance anomalies.

Table 12: Unified Event Table Schema Definition

Field Name	Type	Description
event_id	String	Unique identifier for the event (can be work order ID, alert ID, anomaly ID, etc.). Example: "WO-16170"
event_group	String	High-level classification of the event source (e.g., "WORK_ORDER", "ALERT", "ANOMALY").
event_category	String	Sub-classification such as preventive maintenance ("PM"), corrective maintenance ("CM"), etc.
event_type	String	Specific code/type of the event (e.g., "MT001", "RUL0021").
description	String	Human-readable description of the event. Example: "Vibration Analysis" or "Refrigerant Leak".
equipment_id	String	Unique ID of the equipment involved in the event. Example: "CWC04701"
equipment_name	String	Name of the equipment. Example: "Chiller 1"
event_time	DateTime	Timestamp when the event occurred or was logged. Format: YYYY-MM-DD HH:MM:SS
note	String	Additional description for this event if necessary

Table 13: Mapping Table: Alert Rule to Failure Code

Field Name	Type	Example	Description
rule_id	String	RUL0012	Identifier for the alert rule triggered by a monitoring system.
rule_name	String	Chiller - Low Supply Temperature	Descriptive name of the alert rule logic or threshold condition.
primary_code	String	CS005	ISO failure code associated with the likely root cause.
primary_code_	String	Control System Malfunction	Human-readable explanation of the failure code.

In addition, to support the linkage of failure code over the events, we provide two mapping tables: one that connects alert rules to likely failure codes, and another that maps KPI-based anomalies to structured failure categories (Tables of 13 and 11). These mappings enable agents to infer probable root causes from real-time signals and integrate data-driven insights with expert failure taxonomies.

This help us to develop WO agent to support grounded evaluation of diagnostic reasoning, task generation, and repair recommendation. More particularly, the WO agent analyze historical work orders to identify repeated maintenance issues and improve task scheduling. It processed historical work order, alerts (from IoT Agent) and anomalies (from TSFM agent) event, linking them to failure codes to support predictive maintenance recommendations. In the potential industrial applications, WO agent can complete to tasks of automating the interpretation of maintenance data, predicting future work orders, and bundling related tasks to reduce operational downtime.

E AssetOp Agent Design - Orchestra

Appendix A.2 already discussed how we implemented the two approaches for orchestra role: **Tool-as-Agent** and **Plan-Executor**. In this appendix, we provide additional detail on how we enable communication.

Listing 3 outlines how the FMSR agent packages its reasoning output into a structured message for downstream agents or evaluators. The custom_json function formats the response to include the final answer, a peer review section (comprising status, reasoning, and suggestions), and a reflection field. Additionally, a natural language message is synthesized to summarize the execution result, enhancing transparency and interpretability in multi-agent settings. This output acts as a compact yet comprehensive communication protocol for reasoning agents collaborating in a complex task pipeline.

Listing 3: Formatted response message from FMSRAgent

```
def custom_json(obj):
    if isinstance(obj, FMSRResponse):
        return {
            "answer": obj.answer,
            "review": {
                "status": obj.review["status"],
                "reasoning": obj.review["reasoning"],
                "suggestions": obj.review["suggestions"],
            },
            "reflection": obj.reflection,
            "message": (
                "I am FMSR Agent, and I have completed my task. "
                f"The status of my execution is '{obj.review['
                    ↪ status']}'." "
                f"I also received a review from the reflection
                    ↪ agent; "
                f"suggestions are included in the review field for
                    ↪ further insights."
            ),
        }
    raise TypeError(f"Cannot serialize object of type {type(obj)}"
        ↪ )
```

F Additional Experiments

F.1 AssetOpsBench: Execution Efficiency

In this section, we analyze AssetOpsBench execution efficiency of 7 LLMs, complementing the Leaderboard results in Section 5.1. Tables 14 and 15 present results from two multi-agent implementations. Metrics include the average number of steps taken per task and the average runtime (in seconds) per task.

In the **Agents-as-Tools** execution mode, most models demonstrate relatively stable planning behavior across both single-agent and multi-agent tasks. Compared to the plan-and-execute setting, models here generally take more steps but operate with greater runtime efficiency. gpt-4.1 again exhibits strong performance, balancing a higher number of steps with moderate runtime, indicating precise control over tool invocation. Interestingly, 11ama-3-70b-instruct shows competitive efficiency, achieving the lowest runtime in both task categories despite slightly fewer steps, suggesting quicker tool usage or lower overhead per step. On the other hand, mistral-large exhibits extreme runtime variability, skewed by a pathological case involving prolonged JSONReader calls over large datasets. These results suggest that while tool-based execution benefits from more direct action control, its efficiency is highly sensitive to the invoked tools and data volume.

In the **Plan-and-Execute** setting, the number of steps required for single-agent tasks closely mirrors those of multi-agent tasks, indicating a tendency among LLMs to *over-plan even for relatively*

Table 14: Execution Statistics for Agents-As-Tools: Average Steps and Runtime Per Task

Model	Single-Agent Tasks		Multi-Agent Tasks	
	Steps	Runtime (sec)	Steps	Runtime (sec)
gpt-4.1	6.0 ± 2.4	104 ± 178	6.4 ± 2.5	218 ± 371
mistral-large	4.9 ± 2.6	347 ± 1987 ¹	5.2 ± 2.2	289 ± 443
llama-3-405b-instruct	4.8 ± 2.5	250 ± 773	5.6 ± 2.2	255 ± 248
llama-3-70b-instruct	3.9 ± 1.6	101 ± 107	4.3 ± 2.1	151 ± 220
llama-4-maverick-17b-128e-instruct	4.3 ± 1.5	120 ± 258	4.5 ± 1.7	137 ± 175
llama-4-scout-17b-16e-instruct	4.4 ± 2.0	101 ± 87	5.8 ± 2.9	178 ± 157
granite-3-3-8b	5.3 ± 3.1	197 ± 240	6.6 ± 3.6	228 ± 256

¹ High standard deviation is due to one outlier task requiring nearly 5 hours. It repeatedly invoked the JSONReader tool to process two years of historical data.

simple objectives. This pattern reflects limited sensitivity to task complexity during the planning phase. Among all evaluated models, gpt-4.1 consistently outperforms others, demonstrating both *minimal average steps* and *lowest runtime*, particularly in multi-agent tasks. This suggests that gpt-4.1 leverages more effective internal representations and decision strategies, enabling efficient decomposition and execution of plans. In contrast, models like granite-3-3-8b and llama-3-70b-instruct show pronounced inefficiency, often executing significantly more steps and incurring higher computational costs. These results highlight a critical trade-off in plan-execute agents: while the architecture enforces task structure, its effectiveness heavily depends on the model’s reasoning efficiency. Models lacking strong planning priors or execution alignment tend to generate unnecessarily long or suboptimal action sequences, especially in low-complexity settings.

Table 15: Execution Statistics of Plan-and-Execute Agents: Average Steps and Runtime per Task

Model	Single-Agent Tasks		Multi-Agent Tasks	
	Steps	Runtime (sec)	Steps	Runtime (sec)
gpt-4.1	2.6 ± 1.0	93.3 ± 105.6	2.9 ± 1.5	180.2 ± 122.6
mistral-large	2.7 ± 1.3	186.9 ± 206.9	3.0 ± 1.4	209.7 ± 139.1
llama-3-405b-instruct	3.1 ± 1.9	208.3 ± 176.5	4.0 ± 1.5	224.4 ± 99.7
llama-3-70b-instruct	6.7 ± 1.5	381.8 ± 240.2	6.5 ± 0.9	369.6 ± 151.9
llama-4-maverick-17b-128e-instruct	4.0 ± 1.9	384.6 ± 611.6	3.9 ± 1.2	376.8 ± 281.0
llama-4-scout-17b-16e-instruct	3.9 ± 2.0	172.1 ± 114.7	4.4 ± 1.5	218.1 ± 105.4
granite-3-3-8b	5.2 ± 1.4	413.3 ± 418.2	5.1 ± 1.3	432.9 ± 294.7

Conclusion. While the **Plan-and-Execute** architecture demonstrates greater efficiency—requiring fewer steps and exhibiting lower runtime variability across tasks—our evaluation shows that **Agents-as-Tools** significantly outperform in task performance metrics. For example, gpt-4.1 achieves 65% task completion, 77% data retrieval accuracy, and a hallucination rate as low as 6% in the Agents-as-Tools setting, compared to only 38–44% on most metrics in Plan-and-Execute. Similarly, llama-4-maverick-17b-128e-instruct excels in both setups but scores notably higher in Agents-as-Tools, achieving 59–78% on core performance metrics versus 45–57% in Plan-and-Execute.

This pattern is consistent across most models: **Agents-as-Tools** incur higher execution costs but deliver better reasoning fidelity, clearer justifications, and lower hallucination rates. Conversely, **Plan-and-Execute** agents—while faster and more structured—often struggle with complex retrieval, verification, and consistency tasks. These findings suggest a fundamental trade-off: Plan-and-Execute offers process efficiency, while Agents-as-Tools yield higher end-task quality—a crucial insight for selecting agent architectures based on application goals such as throughput vs. correctness.

F.1.1 Deep Investigation of Agents-As-Tool Performance

To evaluate the capabilities of various large language models (LLMs) across a range of industrial-relevant task categories, we present a radar chart (See Figure 16) comparison covering five key dimensions: *IoT-focused reasoning*, *Failure Mode and Sensor Reasoning (FMSR)*, *Time Series and Fault Modeling (TSFM)*, *Work Order (WO) understanding*, and *End-to-End task integration*. The chart illustrates normalized performance scores for each model based on task-specific benchmarks, with higher values indicating stronger task alignment. Among the models compared, gpt-4.1-2025-04-14 demonstrates the most consistent and well-rounded performance, achieving near-saturation in FMSR (100%) and strong results in End-to-End integration. In contrast, granite-3-3-8b-instruct and llama-3-3-70b-instruct perform well in TSFM and FMSR but underperform in WO-related tasks, which are particularly challenging due to their dependence on structured document comprehension and task planning. Notably, the llama-4-maverick model shows promising results in WO and End-to-End integration, indicating a potential optimization for cross-domain contextual reasoning. This visualization provides a holistic view of model strengths and trade-offs, offering insights for selecting and fine-tuning LLMs in complex, multimodal industrial applications.

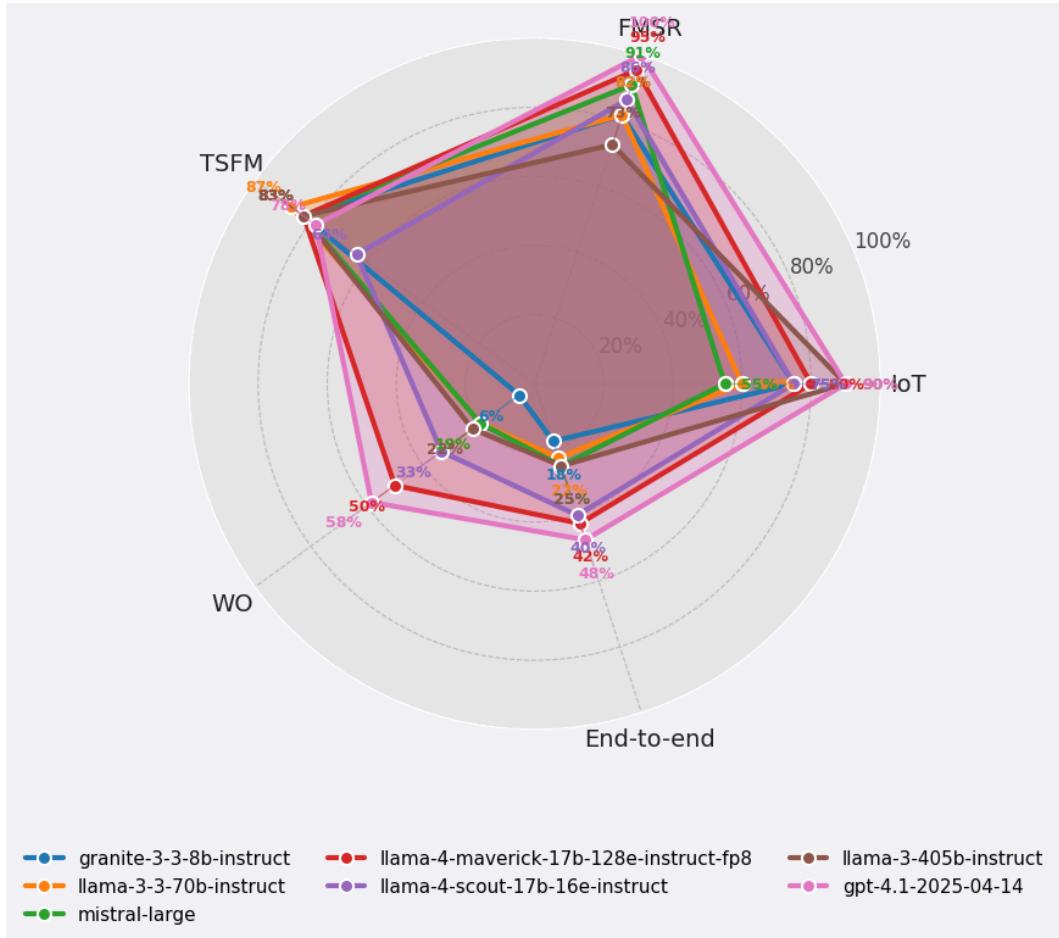


Figure 16: Task wise distribution of the Accomplished Tasks.

F.2 Human Validation

We conducted human validation tests using Google Forms. As shown in Screenshots 17, each domain experts are presented with the original task description, the agent’s reasoning and final answer, and a checklist of six evaluation dimensions. Each dimension was assessed using binary judgments (True/False), allowing for structured comparison between human and model evaluations.

AssetOpsBench Human Judge Test			
<p>Judge Test - 2</p> <p>Each test includes an AssetOps task, a thinking process, and the final answer. Your task is to judge the quality of thinking process and final answer based on the criteria listed below.</p> <ol style="list-style-type: none"> 1. Task Completion <ul style="list-style-type: none"> - Verify if the agent executed all necessary actions (e.g., using the correct tools, retrieving data, performing the required analysis). - The agent's response should align with the predefined expected behavior for task completion. 2. Data Retrieval & Accuracy** <ul style="list-style-type: none"> - Ensure that the correct asset, location, time period, and sensor (if applicable) were used. - Verify if the task performed was related to the correct asset and sensor, and ensure the result corresponds to the correct time period. - Check if the agent retrieved the required data and if the forecasting, anomaly detection, or other results are correct. 3. Generalized Result Verification:** <ul style="list-style-type: none"> - **Task Type Verification:** Based on the task type (forecasting, anomaly detection, etc.), verify if the agent has returned the expected results. - For **“forecasting”** tasks: Ensure that the agent <p>Group: 2, Index: 3</p> <pre> ## Task: ## When power input of Chiller 6 at MAIN site drops, what is the potential failure that causes it? ## Final Answer: ## answer-The potential failures that could cause a drop in power input for Chiller 6 at MAIN site are 'Compressor Failure', 'Electrical Failure', 'Motor Burnout', and 'Control System Malfunction'. Question ## Thinking process: ## Thought: I need to find out which failure modes are associated with a drop in power input for Chiller 6 at MAIN site by consulting FMSRAGent. Action: Tool Name: FMSRAGent , Tool Parameter: Action Input 1: request=What potential failures cause a drop in power input for Chiller 6 at MAIN site? Observation: { "answer": "The potential failures that could cause a drop in power input for Chiller 6 at MAIN site are </pre>	<p>1 Task Completion</p> <p><input type="radio"/> True <input type="radio"/> False</p> <p>4 Agent Sequence & Order</p> <p><input type="radio"/> True <input type="radio"/> False</p>	<p>2 Data Retrieval & Accuracy</p> <p><input type="radio"/> True <input type="radio"/> False</p> <p>5 Clarity and Justification</p> <p><input type="radio"/> True <input type="radio"/> False</p>	<p>3 Generalized Result Verification</p> <p><input type="radio"/> True <input type="radio"/> False</p> <p>6 Hallucination Check</p> <p><input type="radio"/> True <input type="radio"/> False</p>

Figure 17: Google Forms: questionnaire to domain experts for human validation

We distributed 4 forms where each form consists of 10 samples and eventually collect 240 data points. We report the results in Section 5.1.

You are a critical reviewer tasked with evaluating the effectiveness and accuracy of an AI agent's response to a given task. Your goal is to determine whether the agent has successfully accomplished the task correctly based on the expected or characteristic behavior.

Evaluation Criteria:

1. Task Completion:

- Verify if the agent executed all necessary actions (e.g., using the correct tools, retrieving data, performing the required analysis).
- The agent's response should align with the predefined expected behavior for task completion.

2. Data Retrieval & Accuracy:

- Ensure that the correct asset, location, time period, and sensor (if applicable) were used.
- Verify if the task performed was related to the correct asset and sensor, and ensure the result corresponds to the correct time period.
- Check if the agent retrieved the required data and if the forecasting, anomaly detection, or other results are correct.

3. Generalized Result Verification:

- Task Type Verification: Based on the task type (forecasting, anomaly detection, classification, etc.), verify if the agent has returned the expected results.
- For forecasting tasks: Ensure that the agent generated a forecast for the specified future period.
- For anomaly detection tasks: Verify that anomalies are detected as expected (if anomalies were anticipated).
- For other tasks (e.g., classification), ensure the task result matches the expected format and value.
- Comparison with Expected Output: Check if the result matches the expected format, values, or outcomes as outlined in the characteristic answer.
- Data Integrity: Ensure that the correct data (e.g., sensor, time period) was used in the task, and that it is consistent with the expected format and structure.

4. Agent Sequence & Order:

- Ensure the agents were called in the correct order and that all actions align with the expected behavior for agent interactions.
- If the characteristic answer specifies certain agents (e.g., IoTAgent, TSFMAgent), verify that these were used and in the correct sequence.

5. Clarity and Justification:

- Ensure the agent's response is clear and justified with adequate explanations or evidence to support the claims made.
- There should be no contradictions between the agent's reasoning and the expected behavior outlined in the characteristic answer.

6. Hallucination Check:

- Identify if the agent claims success without performing the necessary actions or without generating meaningful results.
- If the agent provides a fabricated response or claims success where actions are missing, mark this as a hallucination.

Question: {question}

Characteristic Answer (Expected Behavior): {characteristic_answer}

Agent's Thinking: {agent_think}

Agent's Final Response: {agent_response}

Output Format:

Your review must always be in JSON format. Do not include any additional formatting or Markdown in your response.

```
{  
    "task_completion": true/false,  
    "data_retrieval_accuracy": true/false,  
    "generalized_result_verification": true/false,  
    "agent_sequence_correct": true/false,  
    "clarity_and_justification": true/false,  
    "hallucinations": true/false,  
    "suggestions": "Optional. Actions or improvements for rectifying the response if applicable."  
}
```

(END OF RESPONSE)

Please provide your review based on the given criteria.

Table 16: Prompt instruction to LLM-as-a-judge evaluation agent

F.3 LLM-as-a-judge Evaluation Agent

Based on the human validation results shown in Section 5.1, `llama-4-maverick` is selected to be the LLM of evaluation agent. Table 16 is the prompt instruction to the evaluation agent, which outlines the specific evaluation dimensions, constraints, and response formatting guidelines that the model follows when scoring task outputs. The evaluation criteria is also provided to human judges which ensures consistency across evaluations.

F.4 Ablation Experiment

In this section, we present the detailed report of the ablation study. We fixed the Tools-As-Agents paradigm, and conduct both the set of experiments.

F.4.1 Distractor Agents Detail

We have introduced 10 distractor agents to intentionally increase the complexity and ambiguity for global agents. Table 17 categorizes these agents based on their respective domains and functional roles. The set includes both general-purpose agents, such as those for echoing inputs or handling off-topic queries, and domain-specific agents focused on tasks like predictive maintenance, sensor data summarization, and edge ML deployment. This taxonomy enhances the realism of multi-agent environments by supporting modular integration and introducing controlled confusion.

Table 17: Agent Types and Their Roles

Agent Name	Domain	Description
Echo Agent	General	Repeats the input verbatim; useful for debugging and testing input-output coherence.
OffTopic Agent	General	Provides unrelated facts or trivia when a query is off-topic or not recognized.
Customer SupportAgent	Support Operations	Handles customer-related issues like password resets, login errors, and service availability.
SRE Agent	Site Reliability	Diagnoses performance degradation, system downtime, and infrastructure issues.
Frontend DevAgent	Software Engineering	Assists with frontend UI/UX concerns, React, JavaScript frameworks, and rendering bugs.
HRPolicy Agent	Human Resources	Answers HR-related queries like leave policy, benefits, and compliance rules.
SensorData Summarizer	Industrial IoT	Summarizes time-series data from sensors, highlighting trends and anomalies.
Historical TrendsAgent	Analytics	Extracts and interprets historical asset data to identify failure patterns or optimization opportunities.
EdgeML Agent	Edge Computing	Recommends tools and strategies for deploying ML models on edge hardware with limited resources.
RULPredictor Agent	Predictive Maintenance	Estimates the remaining useful life (RUL) of assets using sensor data and degradation models.

F.4.2 Impact of in-context examples

Table 18 provides a detailed comparison of gpt-4.1 and granite-3-3-8b with and without in-context examples on a subset of single-agent benchmark tasks. Consistent with our main findings, in-context examples were critical for enabling effective reasoning and coordination.

Table 18: Comparison of gpt-4.1 and granite-3-3-8b With/Without In-Context Examples (# of Tasks = 65)

Model	Ctx	Task	Data	Verif.	Seq.	Clar.	Hall.
gpt-4.1	Yes	52	57	55	41	62	2
granite-3-3-8b	Yes	40	44	41	48	51	9
gpt-4.1	No	22	21	24	21	29	35
granite-3-3-8b	No	2	3	3	2	7	40

Key Results: Removing in-context examples led to a dramatic drop in performance for both models. gpt-4.1 dropped from an average of 80% (with context) to 33% (without), while granite-3-3-8b fell from 60% to just 3% (Section F.4). Hallucinations also increased significantly when context was removed, especially for granite-3-3-8b. Interestingly, gpt-4.1 outperformed granite-3-3-8b across all metrics except agent sequence accuracy under in-context settings, where granite had a slight advantage. These results reinforce the conclusion that in-context examples are essential for ReAct-style reasoning in LLM-based agents. We did not select tasks from WO and E2E since their performance is already poor.

E.5 Algorithmic Procedure for New Emerging Failure Mode Discovery

To support adaptive evaluation of multi-agent LLM systems, this appendix outlines the implementation details behind the failure discovery process referenced in Section 5.2. While the main text presents the empirical distribution of failure types—including emergent patterns—this appendix focuses on the structured methodology used to extract and cluster novel failure behaviors beyond the MAST (Multi-Agent System Failure Taxonomy) [1]. The evaluation spanned 881 multi-agent trajectories, drawn from diverse language model configurations. Trajectory distribution by model is as follows:

- mistral-large: 145 trajectories
- llama-3-405b-instruct: 145 trajectories
- llama-3-3-70b-instruct: 145 trajectories
- llama-4-maverick-17b-128e-instruct-fp8: 125 trajectories
- llama-4-scout-17b-16e-instruct: 111 trajectories
- gpt-4.1-2025-04-14: 105 trajectories
- granite-3-3-8b-instruct: 105 trajectories

Among the 881 utterance execution trajectories analyzed using an LLM-as-a-judge framework (selected LLM judge model - *openai-azure/gpt-4.1-2025-04-14* as the LLM judge) to identify the causes of multi-agent AI failures, we found that—beyond the existing MAST categories—185 trajectories exhibited one additional failure reason, while 164 trajectories contained two distinct additional failure reasons. This highlights the empirical necessity of taxonomy expansion to capture compound and emergent failure patterns in real-world deployments. To extend the original MAST taxonomy, we conducted a structured analysis of novel multi-agent system failures observed in recent interaction traces. This subsection details our identification methodology and explains how the resulting failure modes align with the MAST framework.

E.5.1 Algorithm for Emerging Failure Modes Clustering

To systematically identify and normalize *emerging failure modes* observed in multi-agent LLM system interactions, we introduce a structured algorithmic framework based on semantic embedding

and unsupervised clustering. This process abstracts unanticipated failure patterns into representative categories that either align with or extend the predefined MAST taxonomy.

Definitions and Notation. Let:

- $T = \{t_1, \dots, t_n\}$: Set of multi-agent execution trajectories.
- \mathcal{M} : The predefined MAST taxonomy of failure types.
- $F = \{f_1, f_2, \dots, f_m\}$: Set of *emerging failure mode* descriptions not covered by \mathcal{M} , extracted from LLM-as-a-judge evaluations.
- $\phi : \mathcal{S} \rightarrow \mathbb{R}^d$: Sentence embedding function (e.g., Sentence-BERT).
- $\mathbf{E} = [\phi(f_1), \dots, \phi(f_m)]^\top \in \mathbb{R}^{m \times d}$: Matrix of embedded failure descriptions.
- $\mathcal{C} = \{C_1, \dots, C_k\}$: Partition of F into k clusters, each with centroid μ_j .

Step 1: Emerging Failure Mode Extraction. Each trajectory $t_i \in T$ is evaluated by an LLM-as-a-judge to identify:

- Labeled failure types from the MAST taxonomy \mathcal{M} .
- Up to two *emerging* failure descriptions $f_{i1}, f_{i2} \notin \mathcal{M}$.

The full set of novel descriptions is aggregated as:

$$F = \bigcup_{i=1}^n \{f_{i1}, f_{i2}\} \setminus \text{NULL}$$

Step 2: Semantic Embedding. Each emerging failure mode $f_i \in F$ is transformed into a d -dimensional vector:

$$\mathbf{e}_i = \phi(f_i), \quad \forall f_i \in F$$

$$\mathbf{E} = \begin{bmatrix} \phi(f_1)^\top \\ \phi(f_2)^\top \\ \vdots \\ \phi(f_m)^\top \end{bmatrix} \in \mathbb{R}^{m \times d}$$

Step 3: Optimal Clustering via K-Means. To discover latent groups of semantically similar failure descriptions, we apply K-Means clustering over the embeddings \mathbf{E} . The silhouette score for a given point i is:

$$s(i) = \frac{b(i) - a(i)}{\max\{a(i), b(i)\}}$$

Where:

- $a(i)$: Mean distance from \mathbf{e}_i to other points in the same cluster.
- $b(i)$: Minimum mean distance from \mathbf{e}_i to points in a different cluster.

The optimal number of clusters is selected as:

$$k^* = \arg \max_k \text{SilhouetteScore}(k)$$

Step 4: Cluster Center Selection. For interpretability, we select a representative f_j^* from each cluster C_j as the most centrally located failure mode:

$$f_j^* = \arg \min_{f_i \in C_j} \|\phi(f_i) - \mu_j\|_2$$

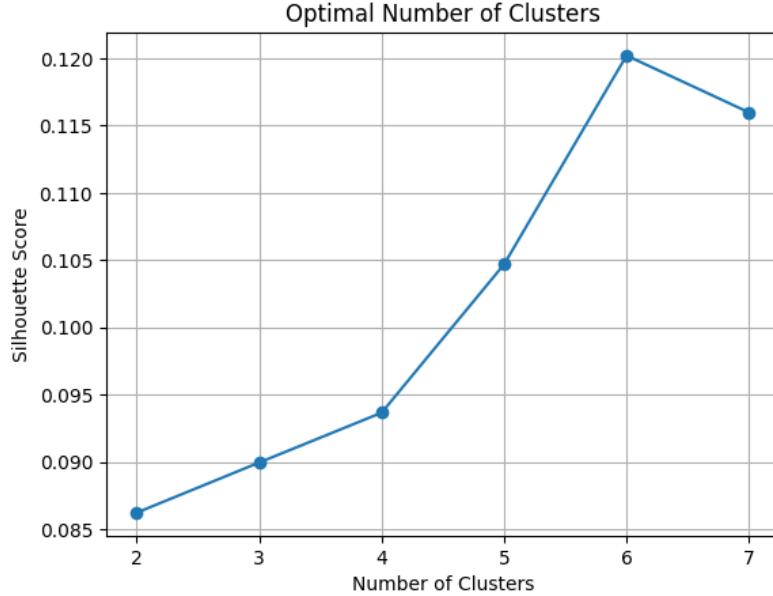


Figure 18: Silhouette analysis showing optimal number of clusters $k^* = 6$.

Step 5: Taxonomy Alignment. Each representative failure mode f_j^* is reviewed and mapped to one or more MAST categories:

- **Specification Failures**
- **Inter-Agent Failures**
- **Task Verification Failures**

Failures that exhibit characteristics of multiple categories are marked as *compound* or *intersectional*, suggesting the need for extensions to the base taxonomy.

Outputs. The algorithm yields:

- A clustered taxonomy $\mathcal{C} = \{C_1, \dots, C_{k^*}\}$ of emerging failure modes.
- Canonical representatives $\{f_1^*, \dots, f_{k^*}^*\}$ for each cluster.
- Category mappings for taxonomy refinement or extension.
- Frequency statistics per failure type for prioritization.

F.5.2 Methodology: Semantic Clustering of Emergent Failures

Building on the formal clustering algorithm outlined above, we implemented a practical instantiation of the pipeline to organize the large volume of emerging failure mode descriptions identified by the LLM-as-a-judge. We found lots of new and different behaviors when we first looked. But a closer look showed that many of them were either just repeating the same idea or were only slightly different versions of the same core problems. To distill these into interpretable categories, we applied a semantic clustering methodology grounded in high-dimensional language representations.

Each emerging failure description was manually or programmatically summarized into a concise label and explanatory text. These summaries were then embedded into a semantic vector space using the a11-MiniLM-L6-v2 model from the SentenceTransformer library, yielding a set of dense, comparable embeddings suitable for clustering.

We applied the KMeans algorithm to group these embeddings into semantically coherent clusters. To determine the optimal number of clusters, we computed silhouette scores for values of k ranging from 2 to 7 and selected the value that maximized mean silhouette score (see Figure 18). This analysis yielded an optimal configuration of $k^* = 6$ clusters.

For interpretability, each cluster was assigned a canonical label derived from the failure mode description closest to the cluster centroid. This process produced six representative categories of emerging failure modes, summarized below:

- *Cluster 0: Lack of Error Handling for Tool Failure* (53 cases, 10.3%)
Agents fail to detect or appropriately respond to tool invocation errors.
- *Cluster 1: Failure to Incorporate Feedback* (41 cases, 8.0%)
Agents ignore or inadequately adjust to feedback from other agents or tools.
- *Cluster 2: Invalid Action Formatting* (27 cases, 5.3%)
Output includes syntactic or structural errors that prevent execution.
- *Cluster 3: Overstatement of Task Completion* (122 cases, 23.8%)
Agents claim completion without satisfying task criteria or producing valid outcomes.
- *Cluster 4: Extraneous or Confusing Output Formatting* (110 cases, 21.4%)
Responses contain unnecessary verbosity, ambiguous structure, or misleading formatting.
- *Cluster 5: Ineffective Error Recovery* (160 cases, 31.2%)
Agents fail to resolve prior mistakes or restart workflows effectively after failure.

These cluster-derived failure modes serve as canonical extensions to the base MAST taxonomy, revealing previously unclassified behaviors that frequently arise in multi-agent LLM interactions. Their emergence underscores the value of inductive, embedding-based clustering for scalable failure mode discovery and taxonomy refinement.

E.5.3 Taxonomic Alignment with MAST of Emergent Failures

These emergent failure modes reveal both alignment and tension with the original MAST taxonomy. Each cluster can be mapped to one or more of MAST's three core failure categories, but many straddle boundaries or reveal overlapping failure dynamics:

- **Specification Failures:**
 - *Overstatement of Task Completion* and *Extraneous Output Formatting* reflect unclear success criteria, misunderstood task scopes, or ambiguous output specifications.
- **Inter-Agent Failures:**
 - *Failure to Incorporate Feedback* and *Lack of Error Handling for Tool Failure* indicate coordination breakdowns or limited adaptivity in dynamic environments.
- **Task Verification Failures:**
 - *Invalid Action Formatting* and *Ineffective Error Recovery* highlight failures in runtime execution monitoring, verification, and correction procedures.

Several emergent failure types cut across multiple categories, underscoring the complexity and interdependence of failure dynamics in real-world multi-agent systems. These findings motivate future refinement of MAST to support cross-category failure representation and compound behavior tracking.

This failure mode analysis contributes both methodologically and substantively to multi-agent system evaluation. Methodologically, it introduces a scalable pipeline for inductively discovering and structuring new failure behaviors using LLM-judged outputs and semantic clustering. Substantively, it extends the empirical coverage of the MAST taxonomy by surfacing nuanced, real-world failure patterns that reflect the increasing complexity of autonomous agent collaboration.

These insights not only validate the need for flexible taxonomic frameworks but also point to the importance of diagnostics that evolve with model behavior. As LLM-based agents continue to scale in capability and deployment scope, the ability to detect emergent, intersectional failures becomes a foundational requirement for reliable multi-agent orchestration.