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# PIONEERING SELF-ADAPTIVE AI ORCHESTRATION ENGINES FOR REAL-TIME END-TO-END MULTI-COUNTERPARTY DERIVATIVES, COLLATERAL, AND ACCOUNTING AUTOMATION: INTELLIGENCE-DRIVEN WORKFLOW COORDINATION AT ENTERPRISE SCALE

**Appa Rao Nagubandi[1]**

[1]*Lead Software Engineer*
ORCID ID: 0009-0005-8424-7071

**Abstract—**Self-Adaptive AI orchestration engines support enterprise-scale multi-counterparty derivatives, collateral, and accounting processes through real-time end-to-end automation and intelligent management of disruptive workflows. In the real-time, multi-counterparty domains, three key characteristics are Architectural: Analytical underpinning for real-time, multi- counterparty deployment of Self-Adaptive AI orchestration en- gines; Intelligence-driven coordination of automated workflows; and Support for real-time process integration and risk-aware collaboration across multiple counterparties. The need for end- to-end immersion and latency independence of trade capture and processing has long been recognized but remains unfulfilled, especially for collateral optimization and margin. When operating with a relatively small number of counterparties, however, it is sometimes possible to bypass this challenge by engineering and adapting separate processes for each counterparty. Such engineered collated workflows then require only to be made visible to the self-adaptive orchestrator engine.

**Index Terms—**Self-Adaptive AI orchestration engines for real- time enterprise-scale multi-counterparty derivatives, collateral, and accounting require rigorous, evidence-based presentation; maintain an objective formal tone with precise terminology and clear argumentation throughout.

## I. INTRODUCTION

Self-Adaptive AI orchestration engines for real-time enterprise-scale multi-counterparty derivatives, collateral, and accounting require rigorous, evidence-based presentation; maintain an objective formal tone with precise terminology and clear argumentation throughout. Artificial intelligence (AI) and related technologies—such as machine learning (ML), natural language processing (NLP), computer vision, and robotic process automation (RPA)—drive consecutive waves of disruptive innovation across diverse industry sectors. How- ever, genuine enterprise-scale adoption is restricted to a limited number of clearly defined problems, and the vast potential for such technologies in driving complex, multi-stage, end-to- end business workflows remains largely untapped. A starting point for addressing this gap is to harness self-adaptive AI orchestration engines across all phases of multi-counterparty derivatives lifecycle management. Orchestration of enterprise-scale processes involves coordinating the capabilities of mul- tiple systems or services in an intelligent manner, typically guided by a combination of human and ”business” domain expertise. The need for timely and reliable coordination is accentuated in end-to-end workflows with sub-processes that are complex, costly, and governed by business relations among multiple parties. Derivatives management, collateral management, and associated accounting tasks constitute a complex workflow that spans several domains, multilayered systems, and multiple counterparties; thus, AI-enabled orchestration is both attractive and challenging.


Fig. 1. AI Agent Orchestrator for Your Enterprise

*A. Background and Significance*

Robust AI orchestration aimed at establishing end-to-end automation over enterprise-scale business functions is critical for harnessing the increased power associated with both AI and automation. These systems require collaborations across systems and domains, and span perception, decision, and action loops. Self-adaptation is a crucial enabler because it allows the orchestration to learn how to operate, stoically handle deviations from normality, and evolutionarily evolve.

There is growing interest from enterprise actors in develop- ing mission-critical AI orchestration layers around business processes for which interaction and coordination among auto- mated workflows—including Data Engineering, Data Analyt- ics, Computing, and Cloud resources—across business units of different organisations are demanded. These demands of increasing interaction and coordination arise for multi-party business functions, such as that found within the handling and management of financial derivatives: Trade capture across business units from different financial institutions, Real-Time Gross Settlement (RTGS) of trades between the transacting parties, multi-party collateral and margin management, and general ledger posting. Handling and management of financial derivatives has complex technical requirements resulting from sub-microsecond processing latencies, sensitivity to risk, and regulatory demand.

## II. Foundations of Self-Adaptive AI Orchestration

End-to-end enterprise-scale self-adaptive AI orchestration engines for real-time derivatives, collateral, and accounting rest on a set of formal theoretical foundations, general architectural principles, and a simpler and more specific Orchestration Engine definition The seven-layer Dynamic Adaptive System model defines self-adaptive behaviour in a system as its capability to perceive changes in its execution environment that either threaten the achievement of its goals or provide opportunities for improving goal satisfaction, reason about alternative adaptation strategies and their anticipated consequences, select the best strategy, execute it, and evaluate its effectiveness using the feedback obtained from the perception of the resulting changed environment. Conversational agents, such as Google Assistant and Amazon Alexa, execute the perception-decision-action loop around every user utterance. Automated workflows for trade execution, treasury management, collateral optimisation, and similar functions can operate in a similar way. The Orchestration Engine definition enhances a promising semi-automated collaboration enabling technology with an integrated planning capability that employs appropriate AI techniques to support and extend the agent-based approach.

**Equation 01: Latency model for real-time trade workflows**
Consider a trade workflow with stages
S=capture, validation, pricing, risk, booking, settlement

For each stage $x_k \in S$
Tk: random processing time (ms) for that stage E[Tk]: expected processing time
L total: end-to-end latency

Assuming serial processing Ltotal=$k \in S \sum T_k$

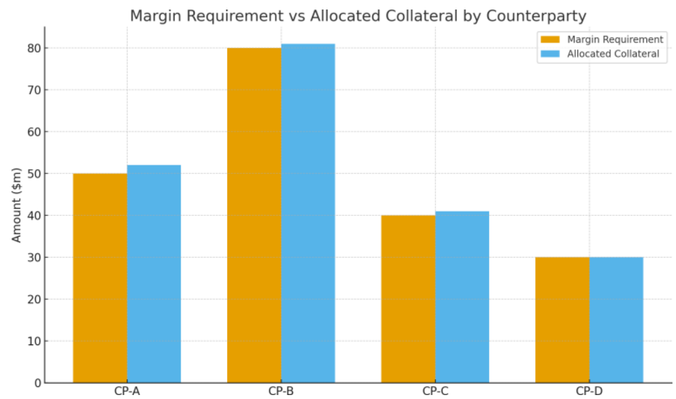


Fig. 2. Margin Requirement vs Allocated Collateral by Counterparty and taking expectations

$$E[L_{\text{total}}] = \sum_{k \in S} E[T_k]$$

*A. Theoretical underpinnings and definitional scope*

Drawing on established research in AI-enabled autonomous systems, enterprise application orchestration, self-organization in complex systems, and real-time adaptive workflow coordi- nation, Self-Adaptive AI orchestration harnesses cutting-edge innovations in corporate education, interaction chatbots, and machine-to-human capability estimation to deliver enterprise- scale end-to-end solutions across multiple operational states and counterparty domains. Application to real-time derivatives, margining, collateral replenishment, and accounting automa- tion illustrates the approach. Self-Adaptive AI Orchestration Engines represent a class of AI-enabled solutions that ad- dresses enterprise-scale application orchestration and work- flow coordination for real-time operations across multiple stages, states, and domains. The perspectives of the enterprise and end-user provide distinct motivations. For the enterprise, the Self-Adaptive AI Orchestration Engine mitigates the es- calating support costs associated with increasingly complex software ecosystems that rely on disparate vendor or in-house applications. For the user, Self-Adaptive AI Orchestration Engines address the information imbalance that inhibits their ability to identify and respond to software or technical issues as they arise by transforming enterprise software from a source of anxiety and frustration into an effortless, Natural Intelligence-driven extension of the user's capabilities.

*B. Architectural principles for enterprise-scale orchestration*

Enterprise-scale self-adaptive AI orchestration operates through a cluster of specialized self-adaptive AI engines responsible for coordinating different processes across a set of heterogeneous systems. While the focus here is specifi- cally on real-time enterprise-scale adaptation of AI orches- tration engines capable of automating end-to-end enterprise- scale derivatives processing across multiple counterparties, the principles can be generalized to other forms of enterprise- scale self-adaptive AI orchestration. Traditionally, business processes or workflows have been modeled and executed using dedicated engines or systems. These Business Pro- cess Management (BPM) systems allow for the definition of complex business processes comprising multiple activities interconnected by control-flow dependencies and constraints. The actual execution of these business processes involves invoking different services that can be performed by different organizations or systems. A specialized BPM system enables the definition of a business process, schedules its execution by invoking services from other organizations or systems and orchestrating them, and monitors its execution for confor- mance and exception handling. The BPM engine can leverage knowledge of different companies' systems to enable cross- organization Business Process Execution. Business processes have also been described as logic-driven processes where the control flow depends on business goals (business rules).

## III. Real-Time End-to-End Orchestration in Derivatives and Collateral Management

Real-time end-to-end orchestration of derivatives and col- lateral management is driven by the objective of minimizing latency through streamlined trade capture, lifecycle manage- ment, and processing. In derivatives, performance benefits can be realized through the orchestration of processing at sub- second latencies encompassing entire trade lifecycles. Such processing requires specialized vendors to support reduced operational latency for a trade's complete lifecycle. In collat- eral management, optimal resource allocation across a multi- counterparty netting set requires joint scheduling of collateral optimization and DvP settlement. 3.1. Trade capture, lifecy- cle, and processing latency considerations Orchestration-aware derivatives and collateral processes operate across diverse phases and sub-processes, which in turn require application support for timely and optimal coordination. In derivatives, the objective of minimizing settlement risk drives investment into PvP and DvP settlement solutions across systems, provided inter-operability and sync across systems are sufficient to support liquidity utilization benefits in collateral management. Such solutions, however, target only a sub-set of the derivative product lifecycle. For the remainder, SaaS solutions from firms such as Automation Anywhere or OpenText-Tabrik provide opportunities to achieve risk-reward trade-offs by minimizing aspects of operational latency. When orchestration-aware, such trade & lifecycle processing requires specialist vendors to minimize latency for the trade lifecycle across all phases, e.g. inception to cancellation. Ultimately real-time processing in the derivatives context is therefore less informed directly by operational latency, but rather the performance of any trade processing component with detailed lifecycle exposure. In collateral management, optimal resource scheduling and allocation combines placement of margin calls and offers with a resource utilization perspective (i.e. minimize total risk/maximum risk efficiency). When directly linked with DvP settlement, it also encompasses synchronization and consideration of collateral resource exposure of remaining positions, across all counterparties in the netting-set. For DvP, timing and placement within the optimization horizon (as well as integration with associated resources), therefore becomes significant. With explicit bilateral agreements at the foundation of derivatives contracts, timing could also allow temporal management of liquidity exposure across counterparties in a margining-set. As a result, true joint optimization across multi- party netting sets considering liquidity exposure, imposes increased resource requirements and therefore complexity.

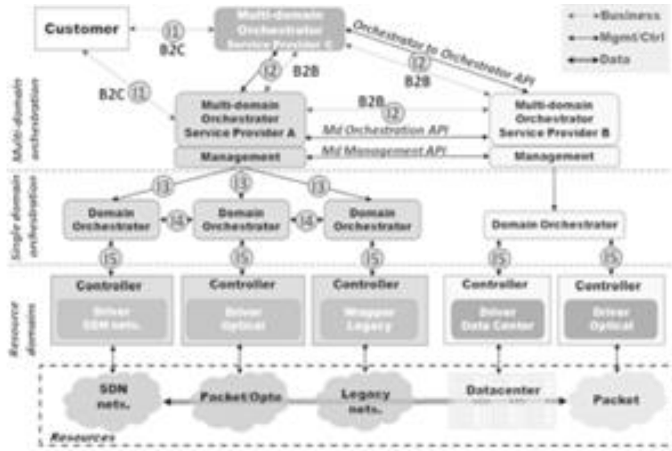


Fig. 3. End-to-end management and orchestration

*A. Trade capture, lifecycle, and processing latency consider- ations*

Real-time enterprise-scale end-to-end derivatives, margin- ing, and collateral management automation requires self- adaptive multimodal AI orchestration at a multi-counterparty level. Trade capture, lifecycle, and processing latency con- siderations inform the architecture. The trade can consist of combined or linked cash legs with either uniform or different currencies. It can have either multiple counterparties or six dif- ferent legs on three legs with different maturities highlighted by their process words 'trade' highlighted like this when a series of swaps also are highlighted. Real-time enterprise-scale end-to-end derivatives, margining, and collateral management automation requires self-adaptive multimodal AI orchestration at a multi-counterparty level. Trade capture, lifecycle, and processing latency considerations inform the architecture. The trade can consist of combined or linked cash legs with either uniform or different currencies. It can have either multiple counterparties or six different legs on three legs with different maturities highlighted by their process words 'trade' high- lighted like this when a series of swaps also are highlighted.

*B. Collateral optimization and margining in a multi- counterparty context*

End-to-end automation of real-time collateral management in the context of regularly tested credit risk exposure relies on an orchestrated but inside-out operational model with business- relevant optimization throughout. Repeatedly evaluating and resourcing the margin and collateral obligations of the full set of counterparty relationships against a given liquidity resource set sets the scale of the operation and bounds that portion of real-time demand. The timing and timing-driven liquidity consumption and production of each partner is itself managed under the observed exposure of the remaining entities using agreed tolerances. Genuine enterprise-scale self-adaptive AI orchestration of the multiplatform, multicounterparty, multi- market derivatives services is underpinned by the simultaneous automation of both set replenishment and margin revaluation workflow. The margins and collateral are dynamically matched against both the asset set which is within the enterprise control and the demand of the partners to ensure that both the antivirus and systemic margin risk are within defined exposure limits. Reclamation and replenishment of the set is actually trivial automation — add useful pieces as they become needed and remove unnecessary items during slack.

## IV. Intelligence-Driven Workflow Coordination

All processing workflows consist of perception, decision, and action loops that must be correctly and efficiently executed. Media-based coordination of decision loops can be implemented in a self-adaptive manner at an enterprise scale for real-time processing workflows, notably under variable operational modes. In contrast, automation of action loops—previously uncovered by Backpropagation Sensing Theory and

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developed in the context of true or indirect learning to both perceive and act in agile, real-time, and closed-loop complex stimulus–response problems—remains largely unexplored in self-adaptive settings. Workflows in risk management operations are planned, executed, and monitored according to enterprise-operational policy, often following a so-called risk-aware scheduling and allocation process utilizing risk, quality, time, cost, and other measures. Self-adaptive AI orchestration engines successfully deployed in other enterprise domains could also support coordination of independent risk-aware workflows operating in response to collateral requirements, notifications of break events, and ad hoc crises. Within the context of derivatives and collateral management, an opportunity exists for self- adaptive automation of static action loops that support trade confirmation, lifecycle processing, collateral management, and collateral optimization in a combination of media-driven and true-indirect learning manner. Or supplied as a service, these action loops create media through which other real-time workflows, independently planned and executed as media- based perception-decision-action chains, can collaborate in the response and recovery from rare, costly, and high-impact break failures linked to missing trades or operational collapses in third-party systems. Such collaborations can incorporate cross-system risk-aware scheduling of non-adaptive workflows across multiple companies while still enabling non-adaptive but risk-aware action loop execution.

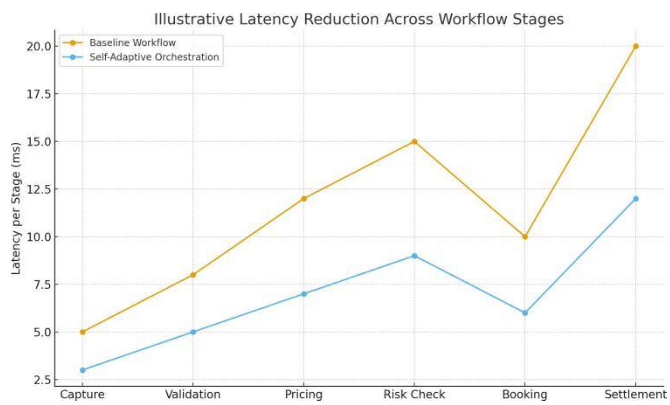


Fig. 4. Illustrative Latency Reduction Across Workflow Stages

| Counterparty | Margin Requirement ($m) | Allocated Collateral ($m) |
| --- | --- | --- |
| CP-A | 50 | 52 |
| CP-B | 80 | 81 |
| CP-C | 40 | 41 |
| CP-D | 30 | 30 |

TABLE I
EXAMPLE MULTI-COUNTERPARTY MARGIN & COLLATERAL TABLE

**Equation 02: Before vs after orchestration**

Let

Tk(0): baseline time at stage $\alpha_k$

Tk(1): time with self-adaptive orchestration Define per-stage improvement factor

$$\alpha_k = \frac{E[T_k(0)]}{E[T_k(1)]} \quad (1)$$

$$\alpha_k = \frac{E[T_k(0)]}{E[T_k(1)]} \qquad 0 < \alpha_k \leq 1$$

Then

$$E[Ltotal(0)] = \sum_k E[Tk(0)]$$

$$E[Ltotal(1)] = \sum_k E[Tk(1)] = \sum_k \alpha_k E[Tk(0)]$$

Relative latency reduction

$$\Delta L = \frac{E[Ltotal(0)] - E[Ltotal(1)]}{E[Ltotal(0)]} = 1 - \frac{\sum_k \alpha_k E[Tk(0)]}{\sum_k E[Tk(0)]}$$

If all stages improve by the same factor $\alpha$

$\Delta L = 1 - \alpha$

*A. Perception, decision, and action loops in automated work- flows*

Automated enterprise-scale workflows that execute prede- fined tasks based on received data yet embed intelligence to respond to unanticipated events constitute realisation of only a fraction of a Self-Adaptive AI orchestration engine's capabilities. Intelligence resides in the engine itself, which can activate and steer such workflows in an appropriate way. Accordingly, Self-Adaptive AI orchestration engines enable the perception-decision-action loop intrinsic to the Intelligent Workflow Coordination component. Loop perception function observes lead-up events for any potential triggers that may activate a workflow conceding to a non-predefined situation.

Available sensor data and triggers from other domains must be monitored, analysed, and correlated to facilitate timely discovery and detection. Scalability of this activity and ob- servability of monitored information become paramount if diverse, real-time-enterprise-wide workflows are to be coor- dinated smoothly. An incoming sensor event is utilized to re- trigger any completed workflow by re-executing its perception function and generating knowledge that applies to the existing situation. For the decision function, the real-time status of managed resources, upcoming needs, and any presents or anticipated resource deficiencies and surpluses are awareness inputs. Self-Adaptive AI play a key role in intelligent decisions related to provisioning or optimally scheduling workflows. The action function initiates resource provisioning in response to identified needs or directs activated workflows to execute the required actions.

*B. Learning mechanisms and adaptation strategies*

Orchestration engines autonomously discovering, learning, and improving execution strategies exploit external feedback as well as runtime and experiential data. Feedback signals from multiple sources, e.g., operating environment, resource execu- tion, and user experience, are crucial inputs for performance- learning algorithms. The choice of signals depends on the learning approach adopted. Reinforcement learning requires the definition of a reward function to quantify adaptation quality, whereas supervised learning maps input features to performance measures. Semi-supervised methods combine performance measures collected in an unsupervised manner with a small set of labeled samples. Performance-learning mechanisms can be used to autonomously devise novel task coordination strategies based on workflow observability. Tem- poral sequences of task activations and their cost measures reflect the performance of currently employed coordination strategies. The learning mechanism first identifies distinguish- able patterns in the sequences over different execution runs and then generates an abstract description of each pattern. Subsequently, one pattern is selected for dedicated tagging so that future workflow executions leveraging the observable sub- workflow corresponding to the selected pattern are tagged and monitored for reinforcement or supervised learning. Finally, the tagged observations are applied to fine-tune control rules that automatically select the coordination strategies during future executions.

## V. MULTI-COUNTERPARTY COLLABORATION AND RISK MANAGEMENT

Enterprises interact with multiple counterparties to exe- cute trades and facilitate payouts through a complex web of relations for product distribution, transaction flow, and funding. Real-time end-to-end enterprise-scale self-adaptive orchestration engines for derivatives, collateral, accounting, and related risk reporting must thus contend with dynamic multi-counterparty, multi-domain workflows that cut across system and organization boundaries. Orchestration engines interact with a multitude of external environment and system components, ranging from other engines to tradable agents and other constraint sources. Encompassing these interactions requires interoperability across systems and domains, which depends on an ability to call agent capabilities directly or indirectly through adaptation and standards—formal or oth- erwise. Orchestration engines must also leverage the percep- tion, decision, action mechanism described earlier to schedule time-critical actions for the enterprise while continuously monitoring risk levels and the allocation of resources. AI techniques enable awareness of risk constraints and the ability to orchestrate risk-aware operations.

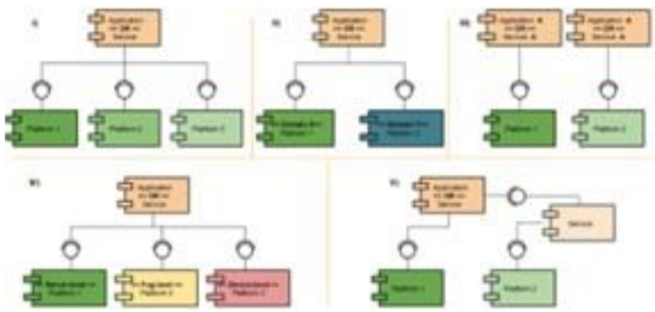

Fig. 5. Interoperability across systems and domains

### A. *Interoperability across systems and domains*

9080 with reference to Figure 16. The core activity of any enterprise involves defining, promoting and realising its business model, and executing its business processes across the enterprise ecosystem. The development and deployment of the enterprise platform must therefore be coupled with a strong capability for business process design and innovation to address the full scope of an enterprise's business interactions and to ensure effective, efficient and trusted service delivery, both internally and externally. The collaborative multi-party AI systems enable an enterprise's business processes to continue to span not only multiple applications and technical domains but also multiple enterprise boundaries. 34247, 9081 and 9082 Support for interoperability can be reinforced by prioritising the identification of shared business interactions in adjacent partner ecosystems and defining them as opportunities to establish collaborative AI solutions that enable efficient and scaled service delivery across enterprise boundaries.

### B. *Risk-aware scheduling and resource allocation*

Operational workflows require near-optimal schedules and effective allocation of resources, including computing and liquidity, to ensure cost-effective execution and to avoid un- wanted risk exposure. Each workflow acts as a connected computation and communication process, constituting a di- rected graph in which the nodes correspond to tasks and the edges define the order of processing. Scheduling should ideally minimize execution cost while guaranteeing certain service levels. For a direct workflow, a simple-time strategy can be leveraged to allocate resources in connectivity, while a steady-state strategy is preferable for complex workflows.

The scheduling problem becomes more complex in multi- counterparty settings during peak loads. By their very nature, risk-aware orchestration engines traverse and orchestrate a wide class of workflows. The execution risk is thus a function of the real-time probability distributions generated by the risk estimator.

Such predictive information can enhance decision- making by enabling the selection of "safer" schedules that are less susceptible to risk variations. Risk distributions are estimated by a dedicated model, while a risk-aware scheduler uses them as additional input. Risk management policies can be incorporated in future work by employing risk budgets.

## VI. ENTERPRISE-SCALE DEPLOYMENT AND OPERATIONS

The deployment and operation of self-adaptive AI orchestration engines within complex corporate, inter-corporate, and multi-vendor environments must facilitate enterprise-scale systems and processes in a robust and resilient manner. The solution set required for enterprise-scale deployment and operation consists of eight conceptual and technical components that underpin the enterprise-scale design principles articulated previously. A three-tiered platform architecture decouples business services from the underlying hardware and software, thereby enabling both horizontal scalability and support for a wide range of workload patterns. Enterprise-scale operations encompass the resilient and efficient monitoring, control, and incident response functions needed to ensure the optimal functionality of AI-powered self-adaptive orchestration engines within an enterprise. Two architecture concepts are considered: myriads of independently usable enablers that, during the process of development, were abstracted into reusable platform services operating on a common foundation; and adaptive engines, which are AI orchestrators, together with the supporting resources, that are required and become operational. Monoliths are working solutions that were built as a single development effort to deliver a specific outcome without attempting to create reusable components. The aim now is to enable them to evolve into components or enablers that can, in the future, provide wider benefits for all products.

**Equation 03: Risk-aware objective**

Define a schedule risk metric Let $d_v$ be the deadline for task $v$

Define delay $D_v = \max(0, s_v + p_v - d_v)$

Let $q_v \in [0, 1]$ be a risk weight We could use

$$Risk(s) = \sum_{v \in V} q_v D_v \qquad (2)$$

Combined cost

$\min(\alpha \cdot \text{makespan}(s) + \beta \cdot \text{Risk}(s))$ where

makespan(s)=maxv(sv+pv) α,β tune latency vs risk

$\sum_v P(\text{break at } v \mid s) \cdot \text{impact}_v$ but that requires a full probabilistic model

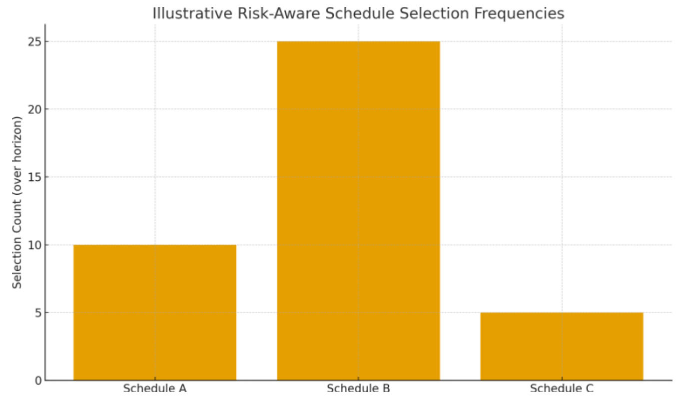

Fig. 6. Illustrative Risk-Aware Schedule Selection Frequencies

### A. *Platform architecture and scalability considerations*

Enterprise-scale enterprise orchestration and monitoring platforms must support ultra-responsive, horizon-less, highly automated enterprise-wide operations across multiple domains. Public cloud platforms offer near-limitless computing re- sources and automated, on-demand provisioning, but self- adaptive AI orchestration engines allow the deployment of workloads in large private or community clouds while support- ing the consumption of cloud services from one or more public cloud service providers. Successful deployment and support of a cloud service at scale requires observability to detect failure modes and abnormal conditions, monitoring services to pro- vide early detection of potential issues and predictable alerts for known issues, management services to address predictable issues before they impact operations, a feedback loop to automatically route work in partially degraded conditions, and a clear and coherent set of operational procedures to diagnose and fix any other issues that may arise. The observability, mon- itoring, management, and incident response services must be scaled to support a large number of consumers and suppliers of responding workloads. An increasingly common architectural style for such support services involves the volume of events being significantly larger than the other workloads, thereby making it practical and cost-effective to deploy those specific services in a separate cloud and/or public cloud.

### B. *Observability, monitoring, and incident response*

Comprehensive observability of Self-Adaptive AI orches- tration engines is crucial for securely and reliably operating enterprise-scale systems. These engines are responsible for the perception–decision–action loops involved in intelligence- driven workflows, and failures in these loops should be both quickly detected and understood. The orchestration engines themselves should therefore expose service metrics that indi- cate the health and performance of the incident-management and action-delivery capabilities; such metrics must be logged, monitored, and tested to facilitate timely detection of prob- lems. Outward-facing API endpoints to monitoring systems must also be maintained to enable monitoring of external interactions with the orchestrated workflows. All changes to the operation of the orchestration engines must follow strict change management protocols, and SLOs must be established for incident detection, diagnosis, and resolution. Moreover, as for all critical, enterprise-scale systems, a simulation en- vironment should be maintained to allow testing of change scenarios, to enable rapid diagnosis of production failures through playback troubleshooting, and to support investigation of production incidents—even at scale—by allowing observers to recreate cloud and data conditions within which the incident occurred.

## VII. CONCLUSION

A common misconception regarding the “self-adaptive” label is that such a capability exists in one specific dimen- sion only, such as processes, agents, or data. In reality, all the functional components listed in the definition—including processes, agents, data, and more—must be self-adaptive. If they were not, then the demands imposed on the system by other self-adaptive components would have to be overcome by static implementations of those non-adaptive components. The presence of a self-adaptive component in any one of these areas opens the door to exploration and exploitation of the respective adaptations through learning mechanisms in any of the other components. The key stand-out is that such exploration and exploitation actually occur under real operat- ing conditions, integrating with and supporting all operational run-time processes—not as a separate off-line process, but as integral to the run-time action. They provide the intelligence needed for advanced workflow automation in orchestration of dynamic workflows, supporting real-time enterprise-scale automation of derivatives, collateral, and accounting across the entire enterprise and beyond, through self-adaptive AI orchestration engines. Detect forward-looking AI process or-chestration technology laid the foundations for the pioneering development of self-adaptive orchestration engines capable of real-time enterprise-scale derivatives, collateral, and account- ing automation across multiple counterparty enterprises.

*A. Future Trends*

The computing, data storage, and bandwidth resources of to- day's broadest cloud computing nodes are inexpensive enough that every enterprise can take advantage of enterprise-scale operation. Bespoke or portable data- and event-conversion systems enable Cloud Data Lake & Glass perimeters to be established, requiring no agents on the massive numbers of trading enterprise. At the same time, continuously-evolving AI techniques and unlocked enterprise-grade self-orchestration have made cost-effective real-time operation achievable in derivatives operations. Underpinned by self-adaptive AI de- struction, orchestration engines enabling real-time, end-to-end, enterprise-scale derivatives, collateral and accounting automa- tion – including continuous eventing of associated subsystems – can learn and adapt during operational use. Latency in derivatives systems originates in trade capture and lifecycle events; True Partners Trading de-synchronizes trade capture and processing and optimally-schedules-collateral for margin- ing across several counter parties, and SOs can reason about the failure pro-ben-listed detected. Pro-posed orchestration is able to re-assign, reschedule, postpone or abort dependent tasks, suspending suspension if necessary.

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