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Advanced predictive autonomous agents for multi-portfolio risk analytics and real-time enterprise P&L decisioning: Self-learning AI systems for multi-counterparty derivatives, collateral valuation, and accounting reconciliation

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Abstract---Predictive autonomous agents enable real-time profit-and-loss decision making for multi-portfolio strategies with derivative products and collateral dependencies. These self- learning systems automatically process data from a multitude of sources, forecast future developments, update models, and assess brokerage, custodian, and counterparty risk. Related technologies guarantee continuous learning, decisioning, and execution. A formal agent-based approach has been defined and implemented, allowing fast simulations of inter-dealer negotiations, default risks, brokering of collateral, and their possible market impact. P&L decisioning in real time with predictive techniques respon- sive to evolving market conditions is paramount. Requests can be formulated for agent-based modeling systems that meet latency and risk control requirements. Such compliant systems provide required inputs for accredited predictive modeling techniques in the P&L space. For market risk reflecting the uncertainty of scenarios and the inability to cover all significant extreme move- ments, time-series forecasting techniques on factors driving risk sensitivities represent a standard procedure. Contingency analysis on sufficient ranges of market risk generating environments is a desirable regulatory recommendation for the supervisory monitoring of systemic institutions and a requisite process for the local and consolidated compliance frameworks of significant investment firms within the European Union.

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Index Terms---Advanced predictive analytics, real-time, au- tonomous agent, derivatives, collateral, liquidity, counterparty risk, edge computing, low-latency, self-learning, self-adaptive.

I. Introduction

Derivatives, counterparty exposures, and collateralized con- tracts present formidable challenges to predictive P&L deci- sioning. Real-time, transparently governed enterprise decision- making for derivatives and collateral valuation across mul- tiple portfolios, while ingestion and action latency are kept extremely low, remain unexplored. Evidence-based, formal instruction sets suitable for academic publishing explore the use of self-learning, predictive, autonomous agents in these contexts. With rigorous predictive modeling, aggregating mul- tiple independent portfolios subject to joint default risks across derivatives and a counterparty network, traders and Identify applicable funding agency here. If none, delete this.

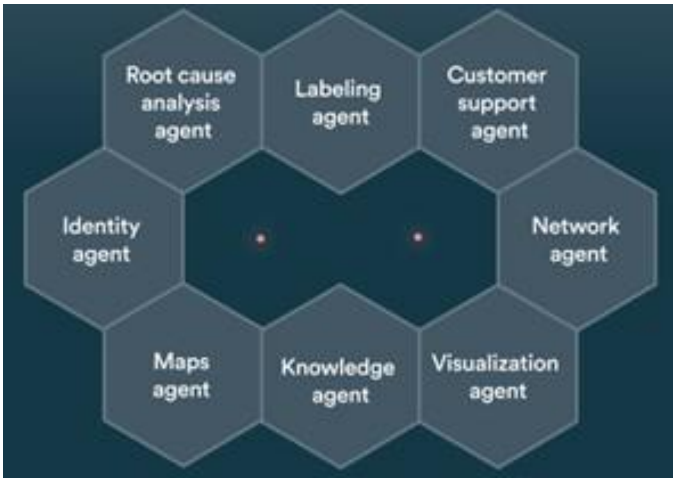

Fig. 1. Autonomous AI Agents in Fraud and Risk Management

risk managers can identify, analyze, report, and reflect upon emerging market, trading, and operational risks. Enterprise Profit-and-Loss (P&L) authorities are traditionally outranked in ultimate responsibility and accountability during market volatility, as valuation models in general use are often ill- equipped for real-time decisioning and adaptive response to emerging market risks. Short-lived markets—the allocation of liquidity, safety, or insurance at exorbitant prices—can usually be detected ahead of time. Due to the lack of formal adaptive modeling of business with external counterparties, emerging market behavior is left to be discerned by judgment rather than routine analytic processes based on predictive models of such phenomena.

A. Background and Significance

Profit and Loss (P&L) statement preparation, as prescribed by Generally Accepted Accounting Principles (GAAP), is necessary for all enterprise accounting. However, these rou- tinely prepared daily, weekly, monthly, quarterly, and annual statements usually contain information that is too old to be useful for business decision-making. The same restriction can be shown for enterprise-wide risk analytics in all organizations with trading activities. Both problems arise from the stated need for confirmed transactions and balances. These serve to give stakeholders confidence in the statement contents. Predic- tive modeling can be used to fill the gap between preparation cycles. The use of predictive models instead of confirmed balances for components therefore allows a proven, automated solution that is acceptable to regulators. Specifically, advance- ments for real-time P&L statement preparation and risk analyt- ics are presented. Regulators and accounting standards permit the use of predictive modeling for intermediate assumptions not confirmed at the time of report preparation. With the advanced, properly gated and forced learning-at-runtime ca- pability of the Real-Time Complex Decisioning Architecture, the predictive models can be permanently infused with changes in risk factors affecting P&L statement preparation or P&L- related risk approvals. Anything affecting the statement can also be audited retroactively. Risk and approval limits can thus be completely managed within the statement-adherent process, producing a predictive, real-time, practically unapprovable, continuously adaptive process.

II. Theoretical Foundations of Predictive Autonomous Agents

The design, calibration, and operation of any predictive autonomous agent encompass key questions about the fundamental nature of autonomous agents within a self- learning paradigm. When and how does an agent learn? How does it incorporate its learning into the decisioning processes? During the model calibration stage, what aspects are essential for predictability and autonomous response? These questions, the answers to which drive the preventive feedback loops within an agent, form the theoretical foundations of the self-learning agents that comprise the overall architecture. An agent learns through an iterative process influenced by external (financial market) state variables. The learning paradigm is continual: an agent retrieves new response data as frequently as possible considering data availability, learns from the incorporated data, and updates its response surface. The design goal is for the agent to converge toward the optimum average real-time response within defined safety constraints. The emphasis on a predictive safety net demands a model capable of predicting the occurrence and magnitude of resulting model gains/losses for failing-agents scenarios within plausible bounds. Cross-validation techniques evaluate each fitted response using out-of-sample data. Training periods reflect considerations of feature-engineering patterns and stationarity. Data or periodical shout windows across the market reflect shallow-bath learning cycles, while testing time spans follow conflict avoidance. Financial-market data must be within explanatory bounds for the model to be trusted. Detection of good or bad calibrations by region supports real-time interpretability of the fitted surface movements.

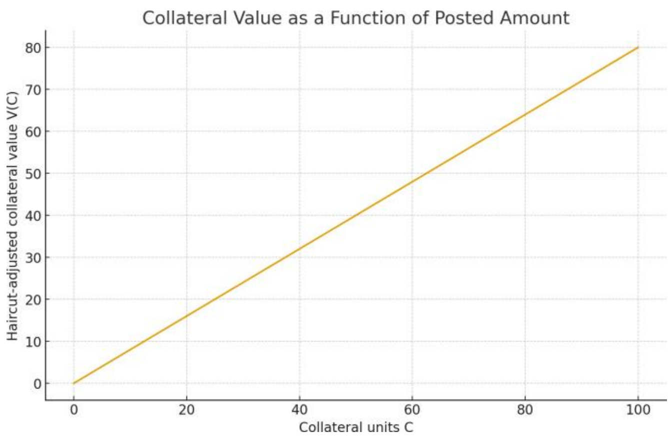

Fig. 2. Collateral Value as a Function of Posted Amount

Equation 01: Collateral Portfolio Value ()VC(i)

The paper defines the total value of collateral posted by bank i as

$$V\ Ci = vCi(CC) + q \sum vq(Cq(i)) \qquad (1)$$

$$+q,\ CC \geq 0 \sum CCi + rC1 + rC2$$

where
CC = amount of cash collateral
Cq(i) = amount of non-cash collateral of type q
$vC_i()$, $v_q(\cdot)$ = valuation functions for cash and each collateral type
rC1,rC2 = additional rate / funding-cost terms

A. Self-Learning AI Systems

Self-learning systems mimic biological learning processes, using experiences and feedback to inform future action. Learn- ing systems that incorporate reward mechanisms formulate a utility function to enhance performance. Although rein- forcement learning directly maps this approach to AI, reward functions are not universally available. The analytic-agent framework is one solution, defining the learning objective and the task to solve in a specific environment. L-learning aligns the agent's model of the world more closely with the actual world, enhancing real-world task performance. The systems use feedback loops to transmit observations of the world, the outcome of their actions, and task performance metrics across several hierarchies. Task decomposition, replaying stored ex- perience, exploration protocols, and teaching signals provide complementary learning signals. Reinforcement learning con- verges asymptotically to the optimal policy under certain conditions. Operating within well-defined constraints ensures safety and predictability. The completion of well-defined tasks provides natural interpretability and aids trust in deployed systems.

TABLE I
EXPOSURE VS CASH COLLATERAL TABLE

Net Exposure E	Cash Posted by Bank i (C C)	Cash Posted by Counter party j (C C (j))			
-80	0	80			
-40	0	40			
0	0	0			
40	40	0			
80	80	0			

B. Multi-Portfolio Risk Analytics

P&L risk aggregates across multiple portfolios. Standard multivariate risk analytics carry significant drawbacks. For predictive decisions when changes to the input volatilities, correlations or concentration estimates are more predictable than the portfolio returns, P&L-at-Risk can also be estimated under a net position assumption. For monitoring, P&L-at-Risk under simple correlation stress tests and the input volatilities set to their longer-term average or extreme observed values are more easily interpretable. Complex interactions often arise between the portfolios of financial enterprises. For instance, entering into new business lines generates new sources of market risk. Those trades can also introduce new dependencies in credit or commodity markets, thereby changing the behaviour of the market risk and introducing credit or liquidity risk. When transactions with other franchise or investment banking units take place, these dependencies may be even larger; however, P and L measures are often expressed without taking such effects into account. The aim is therefore to deploy inferential methods that allow capturing such origins of risk without running a full-scale structural model.

Equation 02: Step-by-step derivation

For each collateral type q, let Market price per unit: Pq

Haircut (percentage discount): $h_q \in [0, 1)$, *hq* ∈ [0, 1)
Units posted by bank i: ()Cq(i)
Then a natural valuation function is

$$v_q(C_q(i)) = (1 - h_q)P_qC_q(i) \tag{2}$$

vq(Cq(i))=(1−hq)PqCq(i)
Haircut deducts a fraction *h*hqof
that value ⇒ effective value = (1−hq)PqCq(i) vq(x)=(1−hq)Pqx
vq(Cq(i))=(1−hq)PqCq(i)
vCi(CC)=(1+rC)CC

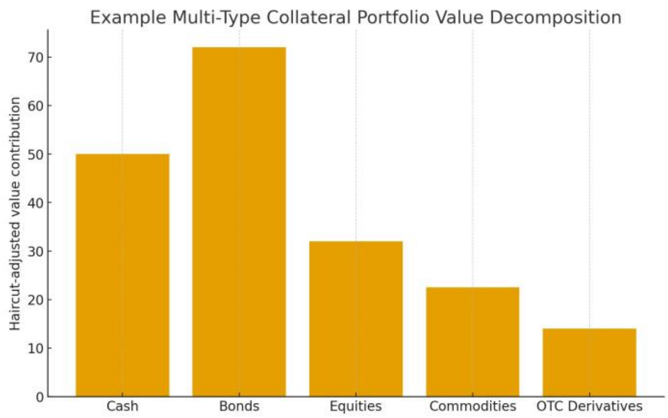

Fig. 3. Example Multi-Type Collateral Portfolio Value Decomposition

Fig. 4. Architecture of Self-Learning Agents for Derivatives Valuation

These agents operate successfully in agent-based simulations of counterparty interactions and – through their analytical power – eventually support the comprehensive risk decision for the entire enterprise in multi-portfolio contexts. The great operational complexity of derivatives and models still makes it impossible to find – within seconds – the value of a single trade and its P and L driver effects for any risk decision. As a result, many transaction costs are still computed every night on

$$\sum_q v_q(C_q(i)) = \sum_q (1 - h_q) P_q C_q(i)$$

many companies' systems simply because the actual market movements are not yet reflected in their systems. All these self- learning agents operate in their designated artificial learning

III. Architecture of Self-Learning Agents for Derivatives Valuation

The architecture of self-learning agents supporting the real- time valuation of derivatives and the collation of the re- spective Profit and Loss (P and L) components subsumes all functional aspects needed for decisioning and learning.
environment and simply learn from all-AI experts and systems at zero-touch.

A. *Agent-Based Modeling of Counterparty Interactions*

Agent-based models simulate the behavior of multiple in- teracting decision-makers to capture system-level outcomes
emerging from the aggregates of individual decisions. Agent- Based Modeling (ABM) is suitable when the behavior of the individuals and their mutual interaction matters to the overall dynamics under consideration. Application of ABM requires a clearly defined set of agents and specification of their characteristics; the decisions they take in response to their information, knowledge and beliefs; the behavior of the environment in which they interact; the processes that govern the sequence and timing of the interactions; and the way in which the outcomes of their interactions determine the state of the environment in the next moment of time. In the context of enterprise controlled derivatives transactions, the selected agents model the bank itself, other financial intermediaries, corporations and Governments. The model embodies an over- arching structure that specifies the fundamental mechanics of party interactions: the negotiation process, the dynamics of default risk, the pattern of margin collateral exchanges, the settings of market variables that are outside the Bank's control, and the way these various players respond to their own circumstances while adapting the risk management ac- tions to whatever strategies they envisage their counter-parties adopting.

B. *Multi-Party Collateral Valuation Mechanisms*

The collateral considered in the models encompasses cash, equities, commodities, bonds, and OTC derivatives. For each bank, it is convenient to define a set of valuation rules for these various collateral types; more formally, the collateral is represented by a set of variables of the form $C^{(i)}$, which denote the amount of collateral of type q posted by bank i. The model includes funding costs for each type of collateral (e.g., haircuts) and its availability in the market.

IV. Data Governance, Quality, and Compliance

Data governance, quality, and regulatory compliance are vital for self-learning AI systems that inform enterprise fi- nancial decisions. Data stewardship, operational integrity, and risk controls ensure soundness, robustness, and auditability of business-critical data assets. Well-managed data provide mean- ingful, timely, and trustworthy information that enables accu- rate real-time P and L decisioning. Data owners safeguard in- formation asset integrity by establishing stewardship roles and responsibilities, realising quality through appropriate controls, enabling regulatory compliance, and instituting operational procedures to minimise risk. Provenance tracking and control regimes ensure completeness, confidence, and completeness in decision-critical forecasting models. Root causes of relevant data-related incidents are documented to identify and mitigate systemic weaknesses. Data quality control parameters provide real-time, continuous monitoring with alerting thresholds to achieve acceptable risk levels. The data lineage framework tracks the authenticity, quality, and completeness of data by listing sources, processing logic, transformations, integration points, and consumptions; enables traceability and validation; and supports investigation into adverse model performance.

Comprehensive model risk management encompasses identi- fication of all relevant risks, adherence to regulatory require- ments, a validation framework that addresses all risk aspects, a dedicated model risk governance structure, and a plan for ex-post back-testing across statistical, economic, and financial dimensions. The validation plan ensures that prudential and enterprise model risks are recognised before operational de- ployment by defining scope, methodology, and governance. Back-testing against actual out-turns is conducted to establish ongoing credibility and integrity of key predictive models, and a set of outranking criteria signals invalid conditions that necessitate a reworking of specific components before further operational use.

A. Data Lineage and Provenance

Comprehensive data lineage is required to demonstrate compliance with both internal data governance policies and external regulatory obligations. For risk analytics, such as market risk VaR, that rely on a broad set of heterogeneous data sources and that also require statistically relevant back-testing, it is essential for regulators to understand the full spectrum of data flows, transformation steps, and data processes—from the originating data sources, through the decision or business intelligence processes and procedures, to the end-users of the data. Metadata supporting data- lineage analysis must therefore be designed, populated, and maintained by data stewardship teams and include the syntax and semantics of the data-tested risk models, information on the data-governance function responsible for each data element, a model risk taxonomy, and other controls for model lifecycle management. Historical data records provide the basis for the training, testing, validation, and back-testing of predictive models. Adequate processes and data provenance allow the testing of how the models perform across time tuples throughout the data test set. For example, a calibration window that slides through the historical data can reveal whether predictive performance is maintained as time progresses. Part of the metadata management includes the definition of model risk and the assignment of model risk categories to each produced predictive model, enabling the design of test and validation plans associated with statistical performance measures, back-testing of performance thresholds defined for each model risk category, and the definition of who is authorized to approve model risk validation and back-testing results.

B. Model Risk and Validation

Model validation aligns with the definition of model risk, which concerns losses incurred due to wrongful usage, in- cluding reliance on errorprone outcomes. The model risk taxonomy comprises the dimensions of condition, domain, and quality. Following this framework, the current validation plan adopts a case-oriented approach. Consideration for the outline and the strategy hinges on the consequent validation impact on total model risk, particularly during the preparation and production phases. During preparation, the scaling is small, and back-testing forms the predominant validation criterion. In production, the footprint is larger: at least one model will be in use at any time, and quality control of daily and final valida- tion is paramount. Validation constitutes the examination and certification cluster, performed with frequency proportional to model risk, which enables origination and maintenance for the entire analytic family. Validation determines whether the forecast qualifies for use without prejudice. Satisfactory complete and formal results demonstrate that a forecasting system with a good and interpretable component set produces augmentation paths of adequate length, demonstrating indeed it captures the dynamics of the series with respect to the P and L direction is critical. Back-testing of actual P and L deviations against acceptable outranking criteria examines slowly-varying market conditions, while relation of P and L surprise to rapid deviations of actuals from reconstruction controls high-speed market environments.

V. Predictive Modeling Techniques for P and L Analytics

A set of techniques is required to determine the P and L for all assets, accounts, and portfolios of the enterprise under nor- mal circumstances and for a variety of market situations. The risks directly attributable to the derivatives portfolios should be captured by predictive modeling techniques such that the main drivers of change in those portfolios are directly reflected to the analytical counterparties, and the P and L is responsive to these changes. Most predictive modeling techniques attempt to determine the objective function as a function of distributions of the explanatory variables. Given sufficient training data, one could also attempt to model the P and L directly in a black box fashion. Changes in the underlying distribution cause instability unless data-driven calibration accounts for the variations. Although the calibration effort is just another form of modeling, it seldom adds value commensurate with the effort involved. Understanding the impact of various trading scenarios and changes in economic circumstances should enhance the ability to make sound trading decisions and ultimately improve profitability. Scenario analysis is not a substitute for full-scale risk analytics; however, guidelines gleaned from scenario impacts should be invaluable inputs to the decision-making process. Moreover, decision thresholds need to be set to identify extreme events beyond which the risk becomes intolerable and prompt action is required. Triggers for shock testing the profitability across alternative portfolio positions and for alerting personnel to material impending P and L changes clearly depend on the state of the business environment. The links from P and L scenario analysis back to market risk are very real and highly relevant for decision- making.

A. Time-Series Forecasting for Market Risk

The expected profit-and-loss (P&L) distributions from forward-looking models are influenced by market movements. Accurate predictions of these market movements, especially at shorter horizons, enable anticipatory P and L decisioning and subsequent interfacing changes with market transacting and

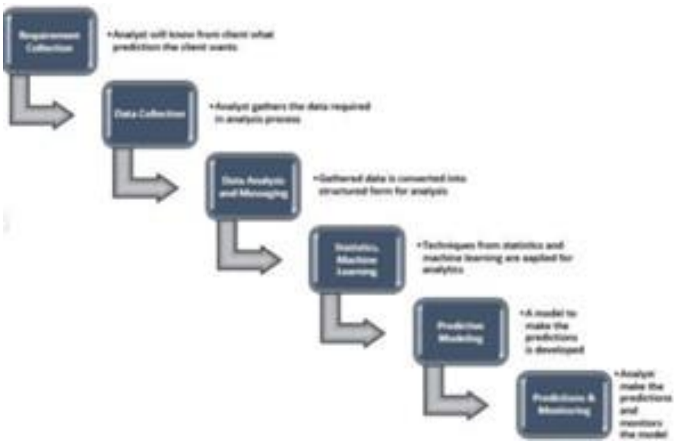

Fig. 5. Predictive Analytics Process

risk mitigation systems. Therefore, one of the most important components in the predictive system is the forecasting of market risk factors. The following sections describe the inputs and algorithms behind the time-series forecasts. A predictive real-time enterprise framework necessitates the exploration and exploitation of the temporal aspect of market risk factors at short time horizons and the statistical characteristics of these histories with respect to the potential information contained in their past values. In general, many financial variables display mean reversion behaviors. Consequently, mean-reverting time- series models are developed and tested for the predicting of interest rates, volatilities, and commodity prices. For market risk factors without mean-reversion characteristics, a selection of alternatives is examined, including the naive, random walk, ARIMA, exponential smoothing, and advanced machine learn- ing models. These time-series models are utilized to produce short-horizon forecasts throughout the forward-looking period of the risk analysis framework.

B. Scenario Analysis and Stress Testing

End-user groups employ scenario analysis to assess the impact of significant shifts in external factors on the enterprise profit and loss (P&L) positions or related key performance indicators (KPIs). Scenarios can be defined along multiple dimensions or as a combination of plausible or extreme events. An event-driven cuboid diagram visualization tech- nique, and soucing simulation results from the time-series model. Scenario results can be analyzed considering defined thresholds and response strategies, overlaid with tolerances supplied by risk committees. Primary and secondary results can be maintained to aid in communicate decisions or assist other groups such as concur incidence management. Stress testing defines pre-determined extreme events or market condi- tions, with impacts evaluated along multiple dimensions. Such analysis is typically regulated for financial institutions but is also commonly applied within non-financial organisations with compliant result outputs. Analysis can be performed for discrete time points or shocks. Pre-defined impacts conforming to Risk Committee plans are independently detailed in a risk model and can be hard-coded to allocating impacts across multiple systems.

VI. REAL-TIME/LOW-LATENCY COMPUTING INFRASTRUCTURES

Low-latency computing is a prerequisite for market risk decisioning within large commercial banks. Latency is the time between receiving a piece of market data and producing its first useful result; the best-known but not only way to minimize latency is to keep the distance between bank servers and market data servers as small as possible. Less obvious is the fact that it is not sufficient that developers of services for low-latency computing focus only on the challenges concerning the services that produce the first useful result. Those services often depend on intermediate processing results that can introduce significant additional delays. Therefore, real-time computing systems that only minimize the latency of the visible part of their processing are vulnerable to future changes that may affect the delay of the intermediate services. The currently prevailing processing paradigm is not naturally suited for low-latency computing. The common approach is to batch-collect data delays, but for real-time computing it is crucial to process the data as soon as they become available: traditional batch-oriented data sources and destinations delay the whole volume retrospectively by the time that it takes to reach the next processing step, and the activity monitoring of batch queues typically ignores the latency of taking initial actions. The result of applying traditional batch data processing concepts to latency-critical applications is the formation of an interminable queue that leads to major losses. To avoid such a situation, production services must explicitly enforce the non-formation of batches but, being on the critical path, can sustain only low marginal loads over short time-frames without service degradation from instability.

Equation 03: Simplified derivation of a symmetric collateral rule

Let's derive a clean symmetric rule

—E— = total cash posted

We also want only one side CC=E+,CC(j)=(−E)+.

Check the two cases Case 1: ≥ 0E ≥ 0.

Then +=E+=E, (−)+=0(−E)+=0

⇒ CC $= E$ (bank i posts), CC(j) $= 0$.

Total collateral posted equals $|E| = E$, as desired Case 2: ¡0E¡0
Then +=0E+=0, (−)+=−¿0(−E)+=−E¿0
$\Rightarrow$ CC $= 0$, CC(j) $= -E$ (counterparty posts) Again, total posted equals $|E| = -E$

A. Streaming Data Pipelines

Achieving low-latency decisioning requires an architecture capable of processing very large volumes of rapidly changing data. Streaming data pipelines can cover use cases where

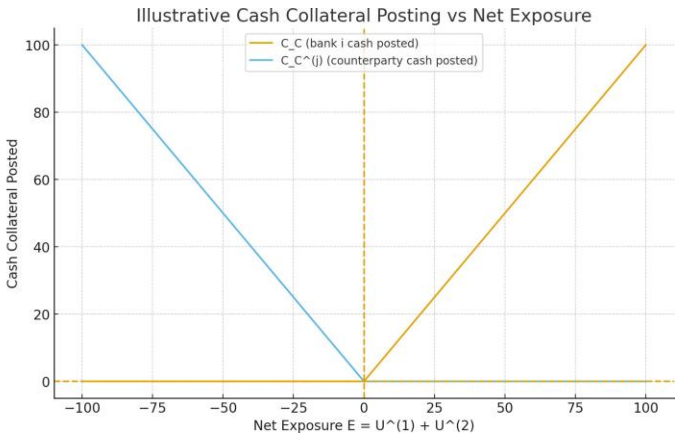

Fig. 6. Illustrative Cash Collateral Posting vs Net Exposure

incoming data must be ingested, processed, and delivered for consumption with low latency. Primary characteristics of streaming data pipelines can be summarized as follows. Data sources emit data records continuously. Data records may be sent by external systems, sensors generating time-related data, or versions of products that are frequently updated. Incoming data records continuously feed an ingestion stage. Within the ingestion stage, data records are validated, transformed, and enriched. After preparation, data records are sent to one or more stream-processing functions for transformation and aggregation to prepare the data for consumption. Processed data records are stored into queried layers, data marts, or data lakes to be available for batch systems. The data movement can run on a defined cycle (mini-batch) or drive a specific process (event-based). Depending on the workload profile, these components may be implemented using services that enforce an SLA for latency and/or data loss. Due to the nature of arriving data records, an appropriate segmentation has to be defined to process data by small batches while keeping the latency within acceptable levels to meet the business objectives. The wheels of a car generation plant report their dimensions every second. If the mean of the dimensions gets out of a defined region, an action should be performed to investigate the problem; therefore, the system has to process the reported data during small windows of time, for example, one minute. In contrast, the average volume of data from data centers may be around 200 records every 10 minutes; however, if the response time of any application exceeds a defined value, the control script must execute an action.

B. Edge and Cloud Trade-Offs

Key factors influencing placement of computation resources for low-latency, real-time/low-latency P and L computation include minimization of distance and hop count between events and their usage, data protection and regulatory re- quirements, and cost of processing. Docker containers run- ning in scalable open cloud services are the easiest, most flexible, and cost-effective option for deployments with low- latency and secure data protection requirements. Complex
architectures enabling rapid response enabling decision latency constraints and regulatory compliance express also through governance policies initiative requiring native services with dedicated private

networks. The dynamics of risk premium and deep learning, prediction, and valuation of surface with P and L decisioning dynamics naturally requires native on- premises or edge computing resources. Trading books with large amounts of transactions can be processed at edge nodes, trading decision supported by near-zero-latency computation help profitability. In some cases where exploration constraints, management computation costs require risk adjustment of no- recommendation zones. Training of prediction, valuation or other tactical learning model for secondary load production could either activate and machine or enforce double model- consistency.

VII. Conclusion

Insights into the architecture of self-learning agents exe- cute predictive modeling essential for forecasting evolving corporate P and L attributes in real time or at low latency. Different branches of a multi-portfolio asset configuration serve immediate counterparties that collectively enter into a transactional P and L relationship with the enterprise. Several models developed during the supervisory review process, articulated elsewhere, forecast the market risk components, while subsequent sections detail transaction scenario definition and approvals, P and L sensitivity by scenario analysis and stress-testing, and aggregation of scenario-based forecasting findings to enterprise-level scope. Trends in the industry outside the organization are shifting towards the adaptation of advanced AI systems. Enterprises are engaging developers to implement digital twins or store-and-forward solutions. Such approaches usually lack prediction capabilities, meaning that forecasting P and L at a market cycle timescale is impossible. Consequently, these systems fail to meet the requirements for smart surveillance of P and L at risk, cannot execute P and L-under-uncertainty analytics under self-defined risk control methodologies, and, above all, lack the ability to reacquire real decisioning capabilities. Furthermore, many don’t generate sound P and L-by-scenario analysis and are even prone to declaring an important breach out of scope for technology!

A. Emerging Trends

Increasing attention to derivatives and collateral in enter- prise profit-and-loss accounting decisioning has led to the development of predictable and interpretable self-learning systems. Simple implementations have proved effective, es- tablishing sound heuristics and approximations. Supported by findings from machine-learning research and by developments on streaming data infrastructures, these systems can now be extended to more complex models, including transaction- based autonomous prediction of pricing, counterparty inter- action, and collateral representee—multiple-party pricing at transaction level across several portfolios coupled by mar- gin replicating collateral uses. More detailed implementations capable of explaining their heuristic underpinnings might soon also be available. Areas requiring further exploration include the relatively user-friendly domains of price, volatility, and correlation prediction under uncertainty; consideration of manually defined P and L-impacting scenarios; execution of scenarios requiring high-speed interrogation of P and L analytics; and development of automatic P and L-valuation- control systems (similar to previous developments in removed- market execution). Insistence on acceptable operating margin between realistic worst-case values is likely to lead to in- creased reevaluation of asset-lending, collateral substitution, and liquidity-arrangement strategies. These trends point to a future in which more stress tests more often and broader collat- eral portfolios become the norm, and more derivatives become collateralized or at least margin-traded, with funding risk remaining systematically imposed through noncollateralized- at-market counterparties.

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