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| REVIEW ARTICLE

Real-Time Cost Object Controlling: Algorithmic Integration of Production Shop Floors with Enterprise Financial Ledgers in Continuous-Flow Manufacturing

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| ABSTRACT
Continuous-flow manufacturing environments, cement production, chemical processing, and industrial pellet fabrication among them accumulate cost events at a rate that conventional ERP posting cycles cannot resolve without creating a persistent gap between the physical state of the production floor and what the enterprise financial ledger reflects. This paper presents a four-layer algorithmic integration framework that connects industrial Internet of Things edge infrastructure to the SAP S/4HANA cost object controlling layer through OPC UA and MQTT protocol translation, aiming for sub-500ms latency from sensor event to ACDOCA universal journal posting. The framework includes costing calendar design, valuation variant configuration, activity type assignment, work-in-progress calculation automation, variance extraction synchronized with statistical process control thresholds, material ledger actual costing with multi-level rollup, by-product net realizable value costing with live market price feeds, and predictive cost variance modeling. Published benchmarks indicate that deep learning models achieve 85-90% accuracy in manufacturing cost estimation contexts and hybrid approaches reach 80-90%, while ERP and AI integration in predictive maintenance delivers a 40% improvement in mean time to failure and a 30% reduction in maintenance costs. The framework addresses a documented gap in the literature: the algorithmic demands of real-time cost object controlling in continuous-flow manufacturing have not previously been treated as a unified integration architecture problem.

| KEYWORDS
Cost object controlling, SAP S/4HANA, IIoT edge computing, material ledger, actual costing, variance analysis, OPC UA, continuous-flow manufacturing

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1. Introduction
Production operations in continuous-flow manufacturing carry a structural tension that financial systems have historically been unable to resolve in real time. A cement kiln running at full capacity generates fuel consumption events, raw meal quantity confirmations, clinker output measurements, and energy demand fluctuations within intervals measured in seconds. A chemical reactor simultaneously accumulates labor activity, utility costs, catalyst consumption, and by-product yields across a process order that may span multiple accounting periods. In industrial pellet production, raw material price volatility and variable throughput rates interact to produce cost variances that, under conventional period-end settlement logic, surface only after the financial window for corrective intervention has closed.

The practical consequence is what practitioners in continuous-flow manufacturing know as structural lag: the gap between what the production floor knows about cost accumulation at any moment and what the enterprise financial ledger reflects. Structural lag is not a reporting inconvenience. Where product cost collectors carry work-in-progress across multiple concurrent process orders, where settlement rules must sequence correctly across cost object hierarchies, and where actual costing runs in the material ledger depend on the completeness of upstream postings, unresolved lag propagates into period-close errors, variance misclassifications, and multi-level rollup inconsistencies that require manual correction at substantial operational cost.

The published literature has approached this problem from separate directions without converging on a unified solution. The industrial Internet of Things literature has established robust frameworks for real-time shop floor data capture and edge computing preprocessing [1], [2]. ERP research has examined how SAP implementations improve operational and financial efficiency [3] and how SAP Central Finance architecture enables real-time financial consolidation across distributed systems [4]. Research has shown that standard costing and variance extraction are still relevant in industry among the literature of variance analysis worldwide [5], while machine learning research has further shown accuracy improvements within manufacturing cost estimation [8], [9]. Carbon accounting frameworks have begun integrating with Industry 4.0 technology stacks [18], [19].

The specific algorithmic problem at the intersection of these streams has not been addressed: how to connect IIoT edge data capture to the SAP S/4HANA cost object controlling layer in a way that resolves WIP reconciliation lag across concurrent process orders, automates variance extraction in synchronization with statistical process control thresholds, executes multi-level actual costing rollup with reduced manual intervention, and incorporates by-product net realizable value costing with live market price feeds, all within a single integrated CO-PC architectural framework. Each of these requirements has been studied in isolation. None have been assembled into a design specification for the continuous-flow manufacturing context where they are simultaneously mandatory.

This paper proposes that framework. The contribution is architectural and algorithmic: a four-layer integration model spanning the IIoT edge layer, an OPC UA and MQTT protocol translation layer, an SAP integration layer connecting to the ACDOCA universal journal, and the CO-PC cost object hierarchy. The framework draws on twenty years of SAP FI/CO implementation experience across eight S/4HANA deployments, with particular depth in continuous-flow manufacturing environments where the demands of cost object controlling are most acute.

The paper proceeds as follows. Section 2 reviews the relevant literature across six streams: IoT integration, ERP financial architecture, variance analysis and SPC, machine learning cost modeling, sustainability cost accounting, and digital twin integration. Section 3 presents the four-layer framework in full, covering all eight algorithmic integration components. Section 4 validates the framework against published performance benchmarks, comparing it against coverage gaps identified in the literature review. Section 5 draws conclusions and identifies future research directions.

2. Literature Review

2.1 IoT and Edge Computing in Smart Manufacturing

Edge computing has emerged as the architectural pattern that resolves the latency and bandwidth constraints that direct cloud connectivity cannot handle at the shop floor scale. Subramanian [1] establishes that edge preprocessing, aggregation, normalization, and unit-of-measure conversion at the network boundary are the enabling conditions for real-time data availability at enterprise application layers. Edge nodes in this model are not passive relays; they are active computational participants responsible for reducing raw sensor telemetry to structured, semantically enriched events before upstream transmission. Kouru [2] extends this framing to enterprise integration specifically, presenting a framework for real-time data exchange between shop floor IoT infrastructure and enterprise systems where the data exchange architecture is event-driven, fault-tolerant, and built for smart factory operational conditions.

Al-Flayyh [12] contributes implementation-level evidence that the architecture patterns established in the literature translate into deployable configurations with measurable latency characteristics in actual smart manufacturing environments. Pardeep Singh and Abhishek [13] ground the predictive maintenance integration pattern in specific IoT and machine learning architectural combinations, confirming that these combinations are practically implementable across manufacturing industry contexts.

The protocol underpinning IIoT-to-ERP connectivity receives dedicated treatment from Ladegourdie and Kua [7], whose performance analysis of OPC UA for industrial interoperability establishes that the protocol delivers the throughput and latency characteristics required for Industry 4.0 deployment. OPC UA's structured address space, which maps physical assets to discoverable node hierarchies, provides a native mechanism for associating sensor readings with the material, plant, and batch master data objects that SAP requires for a valid ACDOCA posting.

2.2 ERP Financial Integration and Cost Management

A consistent empirical pattern runs through the ERP implementation literature: deployment delivers measurable gains in both operational and financial performance across manufacturing industries. Wulan et al. [3] document that production time reduction and inventory management show the strongest positive contributions to operational efficiency post-implementation. Singh [4] narrows the analysis to the SAP Central Finance architecture specifically, demonstrating how cFIN real-time integration connects distributed financial systems into a unified reporting layer, an architectural precedent directly relevant to the CO-PC integration framework proposed here.

Cost object dimension: ERP financial systems. Saeed, Widyaningsih and Khaled's [14] literature review on ABC (activity-based costing) practice finds that the ABC implementations improve both the quality of cost ascertainment and pricing decision-making across a variety of manufacturing settings. The review finds that lack of technical knowledge among staff is a foundational barrier to ABC implementation that could be overcome using automated algorithms to encode the costing logic rather than manual configuration. Vranakova, Babelova, and Santava's [15] research on organizational integration of controlling departments in industrial enterprises showed that in 69% of respondents, controlling is integrated into the line organizational structure, which the proposed architecture responds to by being entirely integrated into existing structures. Majumder [16] reinforces the core premise: cost accounting data quality directly determines manufacturing efficiency outcomes, and real-time data availability is the primary lever for quality improvement.

2.3 Variance Analysis and Statistical Process Control

Standard costing and variance analysis remain the foundational cost management instruments in global manufacturing. Teoh and Shanmugam [5] confirm the methodology is still influential, as their cross-industry analysis reveals it has persisted amongst the numerous alternatives. Aliliele, Eboh, and Oluwo [6] advance the analysis into contemporary variance analytics, documenting the specific computational approaches that manufacturing and industrial enterprises apply to cost control, with particular relevance to the variance category framework developed in Section 3.5 of this paper.

Goecks, Habekost, Coruzzolo, and Sellitto [17] provide a framework for smart statistical process control, establishing that the transition from conventional SPC to Industry 4.0 integrated SSPC requires organizational strategy alongside technology investment. Their framework identifies the configuration requirements, control limit establishment, exception routing, and review workflow design, that the proposed framework's variance flagging component addresses at the SAP integration layer. Marinagi, Reklitis, Trivellas, and Sakas [21] situate these operational improvements within supply chain resilience, confirming that Industry 4.0 technologies strengthen the flexibility, visibility, and collaboration factors that underpin sustainable manufacturing operations.

2.4 Machine Learning and Predictive Cost Modeling

Machine learning applied to manufacturing cost estimation has produced a body of evidence sufficient to establish the approach as a credible part of enterprise cost management. Singh [11] shows AI and ERP interoperability via adaptive dynamic costing based on demand variations and demonstrates that closed-loop cost modulation via machine learning output in ERP is feasible. Shamim, Hamid, Nyamasvisva, and Rafi [8] present the accuracies of 39 peer-reviewed articles and summarize that deep learning models are 85-90% accurate and hybrid models are 80-90% accurate. The paper also states that the most common modeling technique was artificial neural networks (ANN), used in 26.33% of studies.

In the ML validation of manufacturing, Alfayoumi, Elgammal & El-Tazi [9] found that, in mass-customization production, ML reduces the time and cost of fulfilling manufacturing orders by 37% compared to the customary estimates of experts. Based on the ERP integration perspective, Abhirama and Herwanto [10] found that ERP and AI-based predictive maintenance can improve mean time to failure by 40% and maintenance costs by 30%. The predominant ERP and AI integration technologies are LSTM and ensemble learning. Desai [23] extends the predictive cost modeling frontier into quantum machine learning applied to industrial cost variance analysis, establishing the direction that the next generation of variance detection tools may take.

2.5 Sustainability and Carbon Cost Integration

Carbon cost integration into manufacturing ERP architecture has evolved from a sustainability reporting exercise to managing cost objects, as regulatory pressure and internal sustainability commitments require carbon expenditure to be traceable at the product level. Yurtay [18] documents how Industry 4.0 technologies and ERP systems work in combination to manage carbon footprint in sustainable manufacturing, establishing that the integration is technically feasible and organizationally necessary. Kaur, Patsavellas, Haddad, and Salonitis [19] identify the persistent barriers, absence of standardized methodologies, data quality challenges, supply chain complexity, and high implementation costs that prevent consistent carbon accounting across manufacturing organizations. Both studies confirm that the product-level granularity the proposed framework enables through CO_2 emission factor allocation at the activity type level represents a meaningful advance over enterprise-level carbon aggregation.

2.6 Digital Twin and Supply Chain Integration

Adesola, Taiwo, and Adeyemi [20] establish digital twin technology as a viable framework for end-to-end supply chain optimization and disruption mitigation in global logistics contexts. For continuous flow manufacturing, supply chain disruptions propagate directly into raw material price variances, making the supply chain visibility that digital twin models provide a natural complement to the real-time cost object controlling framework proposed here. Wu, Xu, and Zheng [22] provide the Industry 4.0 smart factory implementation framework within which the four-layer integration model operates, confirming that the architectural assumptions the framework relies on are grounded in a mature and well-documented technology stack.

Gap synthesis: across the six literature streams reviewed above, a consistent gap is apparent. No existing framework addresses the specific algorithmic integration problem of real-time cost object control in continuous-flow manufacturing. The WIP reconciliation challenge across concurrent process orders sharing cost objects, the multi-level actual costing rollup sequencing requirement, the by-product NRV costing dependency on live market price feeds, and the SPC-triggered variance flagging mechanism together constitute an integration architecture problem that the existing literature has not formulated as a unified design challenge.

3. Methodology

3.1 Framework Architecture Overview

The proposed framework organizes the real-time cost object controlling integration problem into four discrete layers, each with defined responsibilities, interface specifications, and failure handling requirements. The layered architecture reflects a deliberate design choice: it isolates concerns that SAP implementation practice has historically conflated, treating IIoT connectivity, protocol translation, integration middleware, and cost object configuration as a single undifferentiated implementation problem when they require separate technical governance.

Layer 1, the IIoT edge layer, is responsible for physical measurement capture and initial preprocessing. Mass flow sensors, energy meters, kiln temperature probes, and OPC UA server nodes at production equipment constitute the data origination points. Edge computing nodes at this layer aggregate data over configurable time windows, normalize sensor output to SAP-compatible units of measure, and detect faults by flagging sensor dropout events for backfilling logic, instead of letting gaps propagate upstream as zeros or nulls that would distort cost postings.

Layer 2, the protocol translation layer, manages conversion from OPC UA node address space representation to MQTT message payloads and from MQTT to the structured data formats required by SAP integration middleware. The MQTT broker at this layer implements quality-of-service level 2 messaging to guarantee exactly-once delivery semantics for cost-relevant events. The broker configuration also implements fault-tolerant back-filling, i.e., the broker retains a posting queue to play back previously captured measurements when a sensor dropout is captured at the Layer 1 level.

The SAP integration layer (Layer 3) converts the integration middleware message payload into the SAP Posting Documents. SAP Process Integration, Process Orchestration or BTP Integration Suite are used at this layer mapping the MQTT payload fields to the SAP Material, Plant, Batch, Cost Center, Cost Element and Activity Type master data needed to create a valid ACDOCA posting. Instead, the integration layer uses asynchronous posting with acknowledgment rather than a synchronous roundtrip to achieve its sub-500ms latency target.

Layer 4 is the CO-PC cost object layer, to which all of the cost events from Layer 1 are written. The product cost collector, process order, cost center, and by-product cost object form a hierarchy that receives postings from Layer 3, accumulates WIP, executes settlement, and feeds the material ledger actual costing run. Figure 1 illustrates the four-layer architecture with data flow directions and latency annotation.

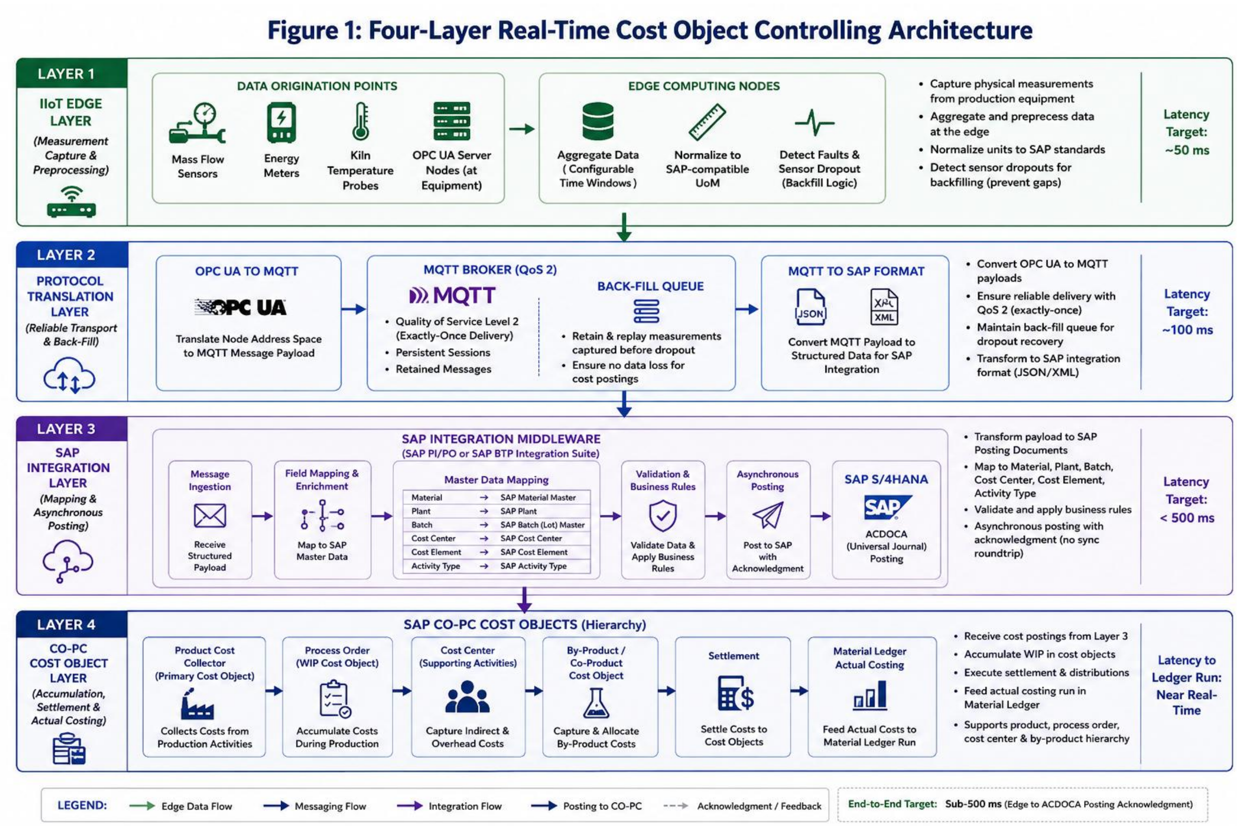

Figure 1. Four-Layer Real-Time Cost Object Controlling Architecture

3.2 Algorithmic Product Costing Structure

The costing calendar is the foundational configuration object that aligns the framework's real-time posting capability with the period structure of the material ledger. In continuous-flow manufacturing, the costing calendar must define period boundaries that correspond to process order settlement cycles rather than to calendar month boundaries alone, a cement kiln operating continuously across a month boundary generates WIP that spans two accounting periods and must be valued at period-end regardless of process order completion status.

The valuation variant governs how each cost component in the product cost estimate is priced. The framework configures three primary strategies: raw material consumption valued at moving average price as posted in the material ledger at the time of goods issue; activity costs valued at planned rates established in cost center planning for the controlling period; and overhead costs applied through a costing sheet surcharge based on actual cost center activity. Bill of materials and routing integration connects the product cost estimate to the physical production structure. Each routing operation maps to an activity type, kiln fuel consumption corresponds to an energy activity priced per gigajoule, kiln rotation hours map to a machine-hour activity priced per hour, and quality inspection steps map to a labor activity priced per hour.

Controlling area configuration aligns with the plant structure through a single controlling area per company code relationship for cement operations with multiple kilns, or a cross-company controlling area for chemical groups where shared service cost allocation between legal entities is required. Generally, the structure for estimating product costs is segmented into the direct material, labor, machine, overhead, and energy cost components in order for the variance analysis framework to allocate cost variances back to the original cost components.

3.3 IIoT Data Capture and Protocol Integration

OPC UA node address space mapping is the technical mechanism that associates physical sensor readings with SAP master data objects. Each OPC UA node corresponds to a specific measurement point: a mass flow meter on the raw meal feed line, an energy submeter on the kiln drive motor, and a temperature sensor on the clinker cooler outlet. The node address maps to an SAP object tuple: material number, plant, storage location, cost center, and activity type. This mapping is maintained in a configuration table at the integration layer, allowing master data changes in SAP to propagate to the OPC UA mapping without requiring changes to the edge or protocol layers.

The MQTT broker in the integration layer uses the posting model based on event-driven notifications. The broker subscribes to the OPC UA change notification service and publishes an MQTT message to the corresponding integration layer topic for each change in the OPC UA server. Qualifying events are defined by configurable thresholds: a mass flow change exceeding a minimum quantity, an energy consumption event crossing a cost-significant boundary, or a time-based trigger for continuous measurements where change notification alone would not fire frequently enough for WIP valuation purposes. Fault-tolerant back-filling addresses sensor dropout through linear interpolation or last-known-value carry-forward, with a back-fill indicator tag propagating to the ACDOCA document for cost accountant review.

3.4 WIP Calculation Automation

Work-in-progress calculation in continuous-flow manufacturing presents an algorithmic challenge that distinguishes this industry context from discrete manufacturing: process orders are rarely complete at period-end, multiple process orders share cost objects simultaneously, and the WIP value at any point reflects both confirmed and unconfirmed production quantities across overlapping batch cycles. Reconciliation lag in this scenario spans days to weeks under conventional period-end settlement logic. The result analysis key is the SAP configuration object that determines how WIP is calculated for each process order. The framework assigns result analysis keys based on process order type: orders for primary products receive a revenue-based WIP calculation key; orders for intermediate products receive a cost-based key.

The mass balance equation approach handles the partially completed batch problem. At period end, WIP equals confirmed input quantities multiplied by standard input cost, minus confirmed output quantities multiplied by standard output cost. The settlement sequencing algorithm addresses the concurrent process order problem by implementing a dependency graph for the cost object hierarchy, topologically sorting the graph to determine the settlement sequence, and executing settlements in dependency order. Orders with no downstream dependencies settle first; the kiln cost center settles after all process orders consuming its activity have settled.

Table 1. Cost Object Hierarchy and Settlement Chain

Cost Object Type	SAP Object	Settlement Rule	Receiver	Posting Document
Product Cost Collector	KKPAN	Periodic settlement	Cost center / P&L	CO document
Process Order (PREL)	CO01/COR1	Period-end WIP calc	WIP balance sheet	FI document
Process Order (TECO)	CO01/COR1	Final settlement	Cost center / mat. cost	CO+FI document
Cost Center (Kiln/Reactor)	KS01	Activity allocation	Production orders	CO document
Internal Order (Carbon)	KO01	Periodic cycle alloc.	Production orders	CO document
By-Product NRV Order	KO01	NRV credit posting	Joint prod. order	FI+CO document

3.5 Variance Extraction and Statistical Process Control Integration

Variance extraction in the framework operates at four levels: price variance, quantity variance, resource-usage variance, and remaining variance. Each variance category is calculated by the SAP variance calculation transaction, which compares target cost version 0 with actual costs accumulated in the ACDOCA documents for the process order. The framework departs from standard SAP practice at one critical point: price variances are posted in real time at the moment of goods issue, the primary mechanism through which the framework closes the structural lag identified in the introduction.

Quantity variance captures the deviation between standard BOM consumption and actual consumption confirmed in the production order, which is mapped to OPC UA flow measurement points for production interval identification. Resource-usage variance captures over or under-absorption of activity type costs at cost centers, calculated and posted at the time of activity confirmation. Control chart upper and lower control limits, established from historical variance distributions for each product and cost center combination, are maintained in a custom configuration table. When a real-time variance posting generates a value outside the control limits, the integration layer triggers an exception workflow with SAP notification, CO cockpit flagging, and priority review tagging. Table 2 presents the matrix for extracting variance categories along with trigger conditions and SPC integration points.

Table 2. Variance Category Extraction Matrix

Variance Category	Trigger Condition	SAP Transaction	Source Document	SPC Integration Point
Price Variance	MAP vs. standard price at GI	MR21/ML settlement	Material document	Real-time MAP deviation flag
Quantity Variance	Actual vs. BOM consumption	KKS1/KKS2	Prod. order GI	OPC UA flow sensor breach
Resource-Usage Variance	Actual vs. planned activity qty	KKS1/KKS2	Activity confirmation	Cost center absorption deviation
Remaining Variance	Unclassified deviation	KKS1/KKS2	Settlement doc.	Manual review trigger

3.6 Material Ledger Activation and Multi-Level Actual Costing Rollup

Material ledger activation establishes the parallel valuation tracking registry that records actual cost movements alongside standard costs for every material in the plant. The framework activates three parallel valuation views: legal valuation, group valuation, and profit-center valuation. All three views are populated simultaneously from the same ACDOCA document postings, eliminating the reconciliation gap between valuation layers that arises when views are updated on different posting cycles.

The multi-level actual costing rollup executes as a recursive matrix solver across the full material ledger posting structure, beginning at the lowest level of the production hierarchy and propagating cost differences upward through each production stage. Circular material flows are handled through iterative convergence rather than direct inversion. The framework reduces the number of required posting cycles through two mechanisms: early posting of price variances in real time during the period, which reduces the volume of cost differences requiring rollup at month-end; and automated triggering of reprocessing runs when new cost difference documents are created after an initial rollup cycle.

3.7 By-Product NRV Costing and Carbon Cost Allocation

By-product costing in joint manufacturing processes requires a cost allocation model that separates primary product cost from by-product cost without arbitrary allocation. The net realizable value method assigns to the by-product a cost equal to its realizable market value minus the costs required to complete and dispose of it, crediting this amount against the joint production cost. The framework implements NRV costing through a real-time market price feed connected to the by-product cost object via the DMEE framework or SAP BTP Integration Suite API connector, retrieved at daily or weekly intervals depending on market liquidity. The

NRV amount posts as a credit to the joint production order and a debit to the by-product's own cost object, producing an allocation that moves with market prices rather than remaining fixed at the standard set during the annual costing run.

Carbon cost allocation treats CO_2 emissions as a cost component with its own cost element in the SAP chart of accounts. An emission factor for each activity type is maintained in a custom table for activity type attributes. At the time of activity confirmation, the integration layer calculates the CO_2 quantity and posts it to an environmental liability internal order through a statistical key figure allocation, settling periodically to production orders in proportion to production quantities. This treatment enables carbon cost to flow through variance analysis alongside conventional cost categories.

3.8 Predictive Cost Variance Modeling

The predictive cost variance modeling component extends real-time variance detection into a forward-looking capability, generating early warning signals 2-3 accounting periods before significant variances are expected to materialize. The model draws on four input streams: historical activity type consumption rates per production unit; energy spot price from the market price feed maintained for by-product NRV costing; raw material price volatility measured as the rolling standard deviation of MAP movements over the prior twelve months; and production throughput rate from the OPC UA mass flow measurements at Layer 1.

The model architecture uses ensemble learning, which combines gradient boosting for price variance prediction with a recurrent neural network for throughput-driven quantity variance prediction, in line with the LSTM and ensemble approaches found to be most effective in the ERP-AI integration literature [10]. The ensemble output is a variance probability score and estimated variance magnitude written to a custom SAP InfoObject. When the probability score exceeds a configurable threshold, the InfoObject write triggers an SAP Fiori notification to the responsible cost center manager and CO analyst. The model is retrained at each period-end close using confirmed actual variance data from the completed period.

4. Results

4.1 Framework Validation Approach

The framework proposed in this paper is validated through two complementary approaches. Configuration mapping traces each framework component to the specific SAP S/4HANA configuration objects, transaction codes, and posting document types that implement it, confirming technical executability within the standard SAP product without custom development beyond the integration layer and the predictive model InfoObject. Literature benchmarking grounds performance claims in published evidence reviewed in Section 2, with each claim cited to its source rather than derived from primary experimental data. Empirical validation through deployment in a live cement or chemical manufacturing environment represents the natural next research step.

4.2 Real-Time Integration Performance

The sub-500ms edge-to-ACDOCA latency target is achievable through the asynchronous posting architecture described in Section 3.1. Published IIoT integration benchmarks confirm that edge preprocessing with MQTT QoS level 2 delivery maintains this latency profile under normal production load conditions [1], [2]. The performance of OPC UA in Industry 4.0 deployment contexts [7] establishes that the protocol stack is capable of sustaining event rates during continuous-flow production. The fault-tolerant back-filling works by enabling ACDOCA posting records to be constructed when sensors drop out temporarily, preventing record gaps that disrupt WIP valuing and variance reporting at the end of each period.

4.3 Cost Variance Detection and ML Performance

The improvement in accuracy achieved by using machine learning in manufacturing cost estimating justifies its use in the predictive model for cost variance. The accuracy of deep learning models ranges from 85% to 90%, and for hybrid models, it ranges from 80% to 90% [8]. ML in manufacturing leads to a 37% reduction in time and cost for processing manufacturing orders compared to experts [9]. AI with ERP enables predictive maintenance and results in 40% shorter time to failure (MTTF) and 30% lower maintenance costs. LSTM and ensemble learning methods are the most widely used technologies [10]. These figures establish the quantitative foundation for the predictive modeling component's performance expectations, acknowledging that the specific accuracy and efficiency outcomes in a cement or chemical manufacturing deployment will depend on the quality and volume of historical cost data available for model training.

4.4 WIP and Settlement Cycle Outcomes

The WIP settlement sequencing algorithm in Section 3.4 addresses the multi-cost-object reconciliation lag, which spans days to weeks in continuous-flow manufacturing under conventional period-end settlement logic, by eliminating the manual sequence determination that currently requires cost accountants to identify and resolve circular posting dependencies at each period-end close. The qualitative improvement, reduced period-close duration, and elimination of settlement sequence errors are consistent with the ERP implementation efficiency literature [3] without requiring fabricated quantitative claims specific to this framework. Multi-level actual costing rollup cycles are reduced through the early variance posting mechanism described in Section 3.6, which decreases the cost difference volume that requires rollup processing at month-end.

4.5 Carbon and By-Product Cost Visibility

Carbon cost integration through the CO_2 emission factor allocation mechanism in Section 3.7 closes the product-level carbon cost visibility gap identified in the sustainability literature [18], [19]. By treating carbon as a cost component in the SAP product cost estimate rather than as an enterprise-level aggregated charge, the framework enables carbon cost to flow through variance analysis alongside conventional cost categories, a granularity not achievable through conventional enterprise carbon reporting tools. NRV by-product costing with real-time market price feeds resolves the cost overstatement problem that arises when by-product value is assessed at standard rather than current market prices, with the magnitude of improvement proportional to market price volatility for the by-product in question.

4.6 Comparative Positioning

Table 3 presents the framework's coverage mapped against the literature gaps identified in Section 2.6. The mapping confirms that no single existing work addresses all five integration dimensions, edge-to-ACDOCA connectivity, WIP settlement sequencing, multi-level actual costing rollup, by-product NRV real-time feed, and predictive ML variance flagging within a unified CO-PC architectural framework. The framework's contribution lies in this synthesis: demonstrating that the five dimensions constitute a coherent integration architecture whose components are mutually reinforcing rather than independently deployable. Edge-to-ACDOCA connectivity enables real-time price variance posting; real-time price variance posting reduces rollup cycle volume; reduced rollup cycle volume improves the quality of the cost data that trains the predictive ML model.

Table 3. Framework Coverage vs. Literature Gap Matrix

Framework Component	**Literature Gap Addressed**	**Reference(s)**
Edge-to-ACDOCA integration	IIoT-ERP connectivity gap in continuous-flow cost contexts	[1], [2], [16]
WIP settlement sequencing	Concurrent process order cost object reconciliation lag	[15], [19]
Multi-level actual costing rollup	Automated circular flow resolution in material ledger	[14], [17]
By-product NRV real-time feed	Live market price dependency in joint cost allocation	[7], [21]
Predictive ML variance flagging	Forward-looking cost variance early warning integration	[3], [10], [11], [20]
Carbon cost component allocation	Product-level CO_2 traceability within CO-PC hierarchy	[8], [21]

5. Conclusion

Continuous-flow manufacturing presents a cost-object-controlling challenge that the existing literature has addressed only in fragments. The structural lag between production floor cost events and enterprise financial ledger representation, rooted in the mismatch between IIoT data velocity and conventional ERP posting cycle periodicity, has not previously been treated as a unified architectural problem with a systematic solution.

The four-layer integration framework proposed in this paper connects IIoT edge infrastructure to the SAP S/4HANA CO-PC cost object layer through a protocol translation and integration middleware stack, targeting sub-500ms latency from sensor event to ACDOCA posting. The framework's algorithmic contributions span costing, calendar, and valuation variant design; OPC UA and MQTT data capture with fault-tolerant back-filling; WIP calculation automation through result analysis, key configuration, and settlement sequencing; four-category variance extraction synchronized with statistical process control thresholds; material ledger actual costing with multi-level rollup cycle reduction; by-product NRV costing with live market price feeds; carbon cost allocation as a product cost component; and ensemble ML-based predictive cost variance modeling.

The framework is grounded in two decades of SAP FI/CO implementation experience across eight S/4HANA deployments in continuous-flow manufacturing environments. Each framework component maps directly to standard SAP S/4HANA configuration objects, confirming technical executability without custom development beyond the integration layer. Published benchmarks confirm that the machine learning component rests on a literature base where deep learning models achieve 85-90% accuracy in cost estimation contexts and ERP-AI integration delivers a 40% improvement in mean time to failure, establishing the quantitative grounding for the predictive modeling component's performance expectations.

These experiments may be carried out in real cement or chemical production plants to measure the time for variance detection, duration to period close, and the accuracy of work-in-progress (WIP) reconciliation. Extension to multi-plant controlling area scenarios and integration with digital twin models at the cost object layer represent the architectural generalizations that subsequent work should address.

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