

From Data to Decisions – Rethinking Smart Manufacturing for High-Mix Systems

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Abstract—High-mix, make-to-order (MTO) manufacturing environments present significant challenges in achieving truly data-driven operations due to dynamic routing, variable cycle times, and non-uniform process execution. While Manufacturing Execution Systems (MES) and Track & Trace solutions have improved operational visibility, they have not enabled the transition from data availability to decision intelligence. This limitation arises from incomplete data architectures and the absence of integrated closed-loop mechanisms.

This paper proposes a five-stage data integrity framework—comprising Digital Plan, Digital Execution, Control, Decision, and Actions—integrated with a nine-dimensional traceability model to ensure complete, contextual, and reliable manufacturing data. The study demonstrates that analytics maturity is structurally dependent on both lifecycle completeness and data dimensional completeness. It further shows that isolated Track & Trace implementations capture discrete events but fail to represent operational reality, resulting in limited diagnostic insight and unreliable predictive capability.

The proposed framework redefines the pathway from data to decisions by establishing a closed-loop cyber-physical system, enabling descriptive, diagnostic, predictive, and prescriptive analytics. By ensuring data completeness and embedding decision and control loops, the framework provides a systematic foundation for self-correcting, intelligent manufacturing systems operating in high-mix, variable environments.

Index Terms—Industry 4.0, Make-to-Order Manufacturing, Data Integrity, MES, Traceability, Closed-Loop Manufacturing, Smart Factory

I. INTRODUCTION

The transformation toward Industry 4.0 has led to the widespread adoption of digital technologies such as Manufacturing Execution Systems (MES), Industrial

Internet of Things (IIoT), and advanced analytics platforms. Despite this progress, many manufacturing systems remain fundamentally reactive, particularly in high-mix, make-to-order (MTO) environments.

MTO manufacturing differs from repetitive production in that each work order may represent a unique product configuration with distinct routing, resource allocation, and processing requirements. As a result, system behaviour becomes non-deterministic, and traditional approaches to process standardization and data modelling are no longer sufficient.

A common approach to digitalization in such environments involves the deployment of Track & Trace systems to monitor material movement and record production events. While these systems provide basic visibility, they fail to capture the full context required for meaningful analysis. Specifically, they do not incorporate process parameters, resource conditions, or execution compliance, all of which significantly influence outcomes.

This limitation leads to a critical gap: data exists, but it lacks meaning.

This paper addresses this gap by proposing a data integrity-driven framework, which ensures that data is not only available but also complete, contextual, and actionable. The framework integrates lifecycle stages and data dimensions into a unified architecture that supports closed-loop intelligence.

II. RESEARCH CONTRIBUTION

This paper makes the following contributions:

1. It establishes that data completeness is a structural prerequisite for analytics maturity, rather than a secondary characteristic.
2. It introduces a five-stage lifecycle framework linking planning, execution, data collection, intelligence, and control.

3. It defines a nine-dimension traceability model as a minimum requirement for contextual manufacturing data.
4. It demonstrates that Track & Trace in isolation is insufficient for enabling predictive and prescriptive analytics.
5. It presents a closed-loop control architecture enabling self-correcting manufacturing systems.

III. COMPLEXITY OF MAKE-TO-ORDER MANUFACTURING

High-mix manufacturing systems exhibit inherent variability arising from multiple sources. Routing paths are dynamic, depending on machine availability, engineering constraints, and scheduling decisions. A component may follow different sequences even within the same production batch, making fixed process models ineffective. Cycle time variability further complicates operations. Machining operations may vary significantly depending on geometry and tolerance requirements, while fabrication processes introduce human variability due to manual interventions. Assembly processes are often dependent on configuration-specific adjustments, leading to additional uncertainty.

The data infrastructure supporting such operations is typically fragmented. Enterprise systems manage orders and planning data, MES systems capture execution data, machine controllers record process parameters, and manual operations often rely on undocumented practices. This fragmentation results in incomplete datasets that cannot support comprehensive analysis.

The consequence is a system where decisions are made based on partial information, leading to inefficiencies, quality issues, and reactive management practices.

IV. CLOSED LOOP INTELLIGENCE- DATA DRIVEN FACTORY

Figure 1 represents an integrated architecture for a data-driven smart factory, structured across three tightly connected layers: the five-stage lifecycle framework, the nine-dimensional traceability model, and the analytics maturity layer. Together, these layers illustrate how manufacturing systems evolve from simple data collection toward intelligent, closed-loop manufacturing and quality optimization.

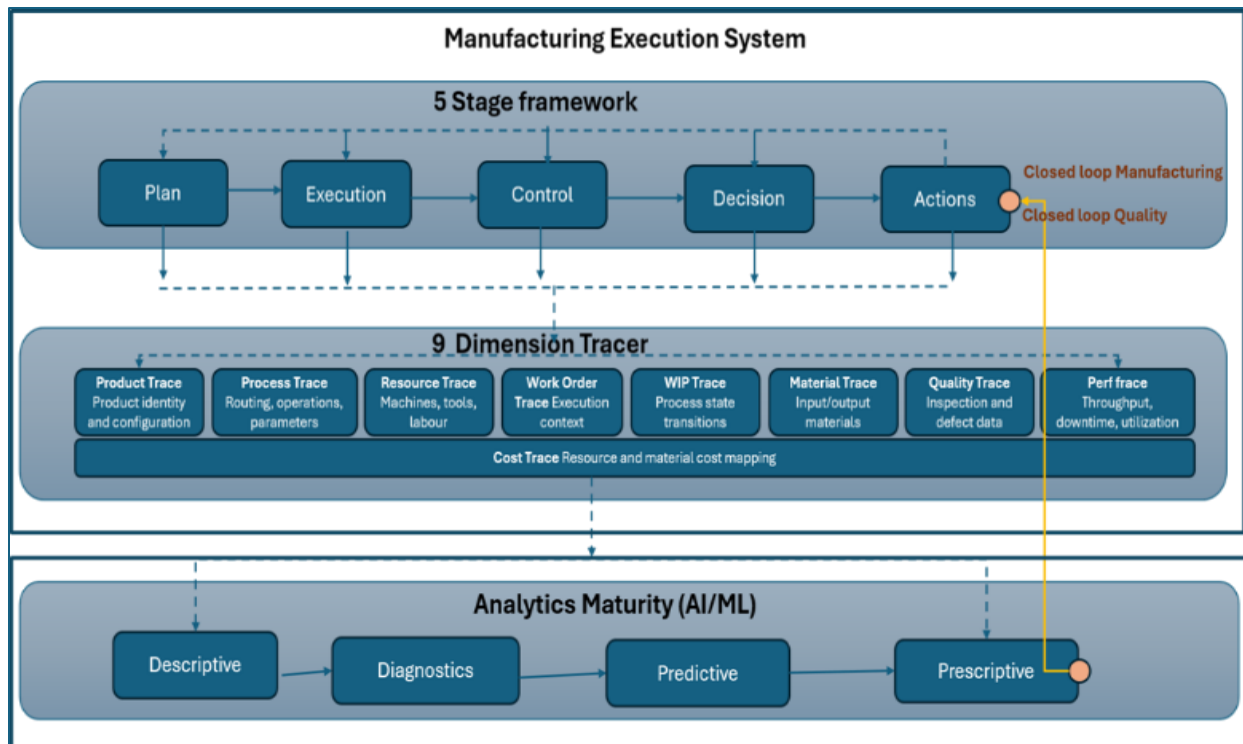


Fig 1- Data Integrity driven closed loop framework

The upper section of the diagram depicts the five-stage framework, which defines the lifecycle through which manufacturing operations are planned, executed, monitored, analysed, and controlled. This layer is the continuous feedback loop, illustrated by arrows connecting later stages back to earlier ones. This feedback ensures that learning from execution and analysis is continuously integrated into future planning, forming a closed-loop system.

The middle section of the diagram illustrates the nine-tracer model, which acts as the data foundation for the entire framework. Each tracer represents a critical dimension of manufacturing data required to capture the complete operational context. These tracers together create a multi-dimensional data model, ensuring that every manufacturing event is captured with full context. The diagram emphasizes that cost trace spans across all other tracers, indicating its integrative role in linking operational data with financial performance.

A vertical connection between the five-stage framework and the nine tracers indicates that each stage depends on and contributes to this data layer. The tracers function as the sensory system of the factory, continuously capturing and feeding data into the higher-level lifecycle stages.

The bottom section of the diagram represents the analytics maturity model, showing the progression of data utilization from basic reporting to advanced optimization.

The diagram shows that analytics maturity is directly linked to the completeness of both the five-stage framework and the nine tracers. Without full integration, the system cannot progress beyond basic descriptive capabilities.

Data-driven manufacturing is achieved only when lifecycle completeness and data completeness are fully integrated within a closed-loop system.

V. PROPOSED FIVE-STAGE FRAMEWORK

The proposed architecture comprises five integrated stages that together form a closed-loop system. A modern Manufacturing Execution System (MES) must incorporate these capabilities to ensure comprehensive and high-quality data collection. This is achieved by digitally integrating planning, execution, control, decision-making, and action processes, thereby supporting both process assurance

and compliance—ensuring that the right activities are performed and that they are executed correctly.

5.1 Digital Plan

Digital Plan establishes the intended state of manufacturing operations by defining product structures, process routes, and resource allocation. It serves as the baseline against which actual performance is measured. In MTO environments, the planning system must support dynamic routing and configurable product structures.

Without a Digital Plan, performance cannot be evaluated because no reference exists for comparison.

5.2 Digital Execution

Digital Execution ensures that defined plans are implemented consistently on the shop floor. It enforces process compliance through structured workflows, machine integration, and operator guidance. This stage is critical in stabilizing system behaviour.

In the absence of execution control, variability increases significantly, and the collected data reflects uncontrolled behaviour rather than designed processes.

5.3 Control

The Control stage represents the mechanism through which execution is governed and stabilized. It ensures that any deviations from the planned process are managed in real time, maintaining consistency and process integrity.

The Control layer enables real-time adjustments to processes, resources, and routing. This stage closes the loop and enables adaptive manufacturing.

Without Control, the system can analyze but cannot act.

5.4 Decision

The Decision layer transforms raw data into insights by identifying patterns, detecting anomalies, and predicting future outcomes. It relies heavily on data quality and completeness from earlier stages.

Without this stage, data remains passive and cannot support optimization.

5.5 Actions

Represent the physical or operational changes applied to the system. These actions may include process

adjustments, re-routing of work orders, or resource reallocation.

VI. NINE-DIMENSION TRACEABILITY MODEL

To ensure data completeness, nine critical dimensions must be tracked: Product, Process, Resource, Work Order, WIP, Material, Quality, Performance, and Cost. Modern MES has shifted its architecture not just being a execution system to holistic integrated Operations (Production, Quality, Inventory, Maintenance) platform with unified data model for operations flexibility, collaborative workflows and data completeness

The tracers include:

- Product Trace, which captures product identity and configuration details
- Process Trace, which records routing, operations, and process parameters
- Resource Trace, which tracks machines, tools, and labor involved in production
- Work Order Trace, which connects execution activities to specific jobs or orders
- WIP Trace, which monitors the state and movement of work-in-progress
- Material Trace, which records input and output materials used in production
- Quality Trace, which captures inspection results and defect data
- Performance Trace, which measures metrics such as throughput, downtime, and utilization
- Cost Trace, which provides financial mapping of resource and material usage

Manufacturing outcomes depend on interactions between these variables. A defect, for example, cannot be attributed to a single factor without considering process conditions, resource state, and material properties.

The absence of any one-dimension results in incomplete analysis. This can be mathematically represented as a multi-variable function where missing inputs prevent accurate evaluation.

VII. ANALYTICS DEPENDENCY MODEL

Analytics capability is directly linked to architecture completeness.

The first level, Descriptive Analytics, answers the question of what has happened. It relies on historical data captured through tracing mechanisms to provide visibility into operations.

The second level, Diagnostics, focuses on understanding why events occurred. This requires correlation across multiple tracers to identify relationships and root causes.

The third level, Predictive Analytics, uses historical and real-time data to anticipate future outcomes. This stage depends on stable and complete data generated through controlled execution and comprehensive tracing.

The highest level, Prescriptive Analytics, determines what actions should be taken. This requires not only accurate predictions but also integration with decision-making and control mechanisms to enforce actions.

This leads to a fundamental conclusion:

Prescriptive analytics is structurally impossible without decision and control integration.

VIII. EXCEPTION HANDLING AND CLOSED-LOOP CONTROL

Manufacturing systems frequently operate under abnormal conditions. The ability to detect and correct deviations determines system resilience.

In the proposed framework, abnormal conditions are detected through trace deviations, analysed in the Decision layer, and resolved in the Control layer. This structured approach enables a transition from reactive to proactive management.

IX. INDUSTRIAL ILLUSTRATION

Consider a machining-fabrication-assembly workflow where defects occur during final inspection. In a basic system, the defect is associated with the last operation. However, this association is misleading because the root cause may originate upstream.

With the proposed framework, data from multiple tracers is correlated, enabling identification of patterns such as defects linked to specific process parameters or machine conditions. Corrective action is then applied through the control system.

X. DISCUSSION

The proposed framework redefines the concept of a data-driven factory by emphasizing completeness rather than data volume. Traditional approaches focus on monitoring, while the proposed approach focuses on understanding and action.

This shift enables manufacturing systems to transition from passive observation to autonomous optimization.

XI. CONCLUSION

This paper demonstrates that data-driven manufacturing is fundamentally an architectural challenge. The integration of lifecycle completeness and data dimensional completeness enables reliable analytics and closed-loop control.

The proposed framework provides a foundation for smart manufacturing systems capable of continuous improvement and autonomous operation.

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