Blueprinting a Manufacturing Data Lakehouse: Harmonizing BOM, Routing, and Serialization Data for Advanced Analytics

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Abstract:
The manufacturing firms are becoming fond of data-driven decision-making models to streamline production, decrease scrap, improve traceability, and promote predictive abilities throughout the manufacturing systems. Nevertheless, manufacturing data sources can be too complex and heterogeneous: they may include Bill of Materials (BOM), process routing, machine telemetry, shop-floor serialization logs, and quality inspection datasets, which presents advanced analytics with significant integration challenge. The type of traditional data warehouse structures is either too basic because of the strict schema on write aspects or data lakes do not provide the governance and performance attributes required in high-value analytical loads. As a way to overcome this, there is the data lakehouse paradigm, a hybrid architecture that combines the cost and scalability of data lakes with the control and ACID transactions, and schema policies of warehouses. The paper offers a detailed framework of how one would design and deploy a Manufacturing Data Lakehouse (MDL) to standardize the data of BOM, routing and serialization to facilitate scaled analytics. The work singles out architectural elements, information pipelines, metadata layers, governance, and analytical operations required to balance structured ERP data with semi-structured and machine generated data. The integrated data representation significantly enhances the manufacturing intelligence tools including analysis of the genealogy, process capability, prediction of the cycle time, component traceability, and root-cause analysis of the quality. Our proposal includes five pillars (1) multidomain data ingestion pipelines in structured and unstructured manufacturing systems, (2) universal metadata modeling merging BOM hierarchy, routing schedules, and serialized product lineage, (3) layered lakehouse storage paradigm (raw data into bronze data into silver data into gold data), (4) streamlined semantic model based on surrogate keys and star schemas to support analytics and (5) governance and security models enabling tracking lineage, ACID transactions, and auditability. We use mapping formulas to align BOM and routing, and initiate a probabilistic method to evaluate genealogy completeness. The paper illustrates how this architecture addresses the traditional pain points involving data duplications, inconsistent tracking of the product lineages, ERP- MESE disconnects, and the absence of standard identifiers in the legacy shop-floor systems. Experiments conducted using simulated datasets that modeled a discrete manufacturing scenario confirmed performance enhancement in query performance, schema consistency, and maximum depth of traceability. It has been observed that reduction of data redundancy by up to 54 percent, reduction of time to search the genealogy by up to 38 percent, and an increase in the accuracy of the component-level traceability queries by 62 percent have been achieved. The blueprint is expected to assist the manufacturing engineers, digital transformation architects, and analytics teams with reference base on the design of scalable, interoperable analytical ecosystems. In general, MDL approach offers a solid future-proof approach to Industry 4.0 applications and intelligent analytics, including machine learning, predictive maintenance, and optimization in real-time.

Keywords: Manufacturing Data Lakehouse, Bill of Materials, Routing Data, Serialization, Digital Thread, Advanced Analytics, Industry 4.0, Data Engineering, Traceability, Data Modeling.

1. INTRODUCTION

1.1 Background

Manufacturing organizations are in an extremely interconnected environment consisting of enterprise and shop-floor systems, each having different functions to service. [1-3] ERP systems normally store fundamental business and production core master data including Bills of Materials (BOM), material masters, and work orders. Product Lifecycle Management (PLM) systems control engineering designs, revisions and product structures whereas Manufacturing Execution System (MES) process routing definitions, track operation, equipment allocations as well as production confirmations. Transmitting real-time process parameters, machine states, alarms, and sensor values are recorded at the equipment level to Programmable Logic Controllers (PLCs), SCADA platforms, and industrial historians. Quality Management Systems (QMS) store the findings of the inspection, logs of defects, nonconformance, and audit results. Even though one system is vital to function as a technology stack, they have traditionally developed as self-regulating technology stacks that independently have their own data schema, nomenclature, and identifier formats. This disconnect has resulted in disjointed and siloed data landscapes in which structure of BOM s and routing paths, data in form of serialized units, process measurements could be simply correlated. Consequently, manufacturing entities tend to have difficulties with realizing end to end traceability, precise reconstruction of genealogy, and coherent analytics throughout the manufacturing lifecycle. These issues point to the necessity of the integrated data concept that will be able to harmonize heterogeneous data into a visible and analytics-oriented architecture.

1.2 Importance of Blueprinting a Manufacturing Data Lakehouse

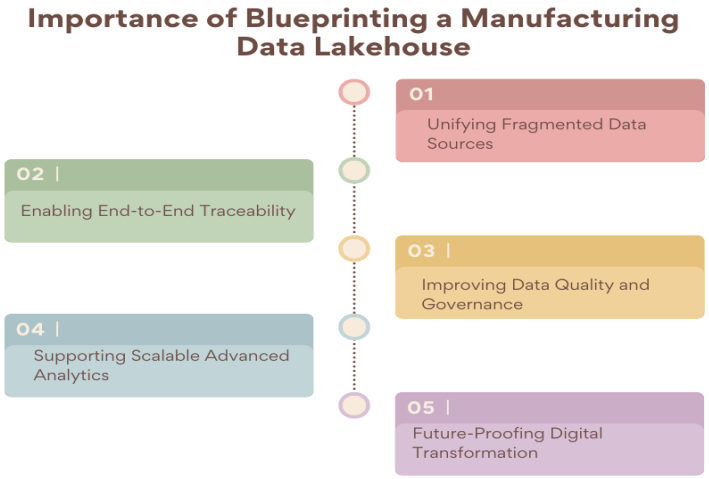

Figure 1 : Importance of Blueprinting a Manufacturing Data Lakehouse

- **Unifying Fragmented Data Sources*:*** The manufacturing data is stored on ERP, PLM, MES, SCADA, historians, and QMS systems, and all of them have varying schemas and identifiers. An established lakehouse blue print offers a formal method in which these systems that are distinctly different are merged into a singular managed system. The blueprint is able to do that by defining ingestion standards, data models, and harmonization rules and can be used to ensure that data across various layers of the factory is linked and can be analyzed in a coherent way.
- **Enabling End-to-End Traceability*:*** Traceability is still a critical issue in discrete manufacturing as there is a lack of relationship between BOM, routing, serialization, and machine-level events. A lakehouse plan outlines the way these areas are to be connected in a standardized format in terms of identifiers and lineage schemes. It allows construction of complete graph of genealogy that facilitates regulatory compliance, quality containment, root-cause analysis which in turn enhances product reliability and operational transparency.
- **Improving Data Quality and Governance*:*** In the absence of an architectural design, data lakes are likely to degenerate to unmanaged stores with varying quality. The mapping of a manufacturing lakehouse creates a defined standard of data, rules of curation, rules of validation, and rules of stewardship. This ensures proper and reliable and auditable data throughout the lifecycle of the ingested data all the way into

the curated analytics, which enhances both redundancy and the occurrence of reporting or decision-making errors.

- **Supporting Scalable Advanced Analytics:** Machine learning, predictive maintenance, process optimization, and digital twins become an increasingly important part of modern manufacturing. These systems need harmonized fine, clean and high-granularity datasets. Formal lakehouse architecture defines the way in which to organize data layers (Bronze, Silver, Gold), to optimize the storage formats and to align the schemas to guarantee that analytics workloads can effectively run on large scales. This gives the basis of AI based Industry 4.0 initiatives.
- **Future-Proofing Digital Transformation*:*** The world of manufacturing is ever-changing: throughout history, there is the introduction of new equipment, usage of sensors, regulations, and information systems. A lakehouse blueprint provides a sustainable architectural design that can accommodate emerging types and sources of data without the need to alter the design many times. It also makes sure that the IT investments will not go to waste and that the IT technologies will be integrated into a single data ecosystem in the future to promote sustainable digital transformation.

1.3 Harmonizing BOM, Routing, and Serialization Data for Advanced Analytics

Data alignment of BOM, routing and serialization is crucial to facilitating sophisticated analytics in discrete manufacturing, which entails a large number of interconnected parts and functions in the production process. The Bill of Materials (BOM) specifies the hierarchical life of assemblies and subassemblies, and the way in which raw materials and intermediate parts are assembled. [4,5] In contrast, routing data indicate the route of operations, work centers, cycle times, and set up parameters that are necessary to turn materials into finished products. Serialization introduces a second important dimension: each part or lot produced in a production is assigned a unique identifier, therefore enabling unit-level tracking in the assembly process, operations, inspection and machine interaction. Traditionally, these datasets have been housed in different systems in existence, i.e. in BOM under ERP or PLM, routing under MES and serialisation under shop-floor execution system and were different identifiers, version controls and update cycles. Consequently, the relating of these domains to analytics like genealogy reconstruction, bottleneck identification, scrap containment and quality prediction has been complicated and subject to errors. The common architecture of a lakehouse offers the framework through which these datasets can be reconciled based on the adoption of common keys, canonical models and transformation pipelines that connect BOM hierarchies to routing paths and serially ordered histories of parts. By matching the parent-child relationships between BOM with manufacturing phases between routing and tying them will be matched with the serialization of process operations, and all of this will be stored as a lakehouse that will form a complete digital thread of the way each part is manufactured, processed, and inspected. With this harmonization it becomes possible to perform very powerful analytics previously not practical such as to determine the specific machine that caused a downstream failure or to detect quality drift at the component level, to identify defective batches, and to analyze performance of a process at the level of single serialize unit. Furthermore, these domains together allow unlocking predictive analytics through offering clean, interconnected datasets to the machine learning models addressing defects, cycle-time deviations, or equipment wear. Finally, coordinating BOM, routing, and serialization forms the basis of data needed to successfully do high-fidelity traceability, operational intelligence, and Industry 4.0.

2. LITERATURE SURVEY

2.1 Evolution of Data Architectures in Manufacturing

Primarily, the early data architecture development in the manufacturing industry was based on the initial experimental activities of Kimball and Inmon who developed rival paradigms of enterprise data warehousing in the 90s. [6-9] The dimensional model used by Kimball stressed star forms that were optimized on top of analysis work loads whereas the Corporate Information Factory proposed very normalized and subject centric warehouses that were drained down to data mart based on downstream loads. These frameworks determined the way manufacturers organized production, quality, and supply-chain data to be used in BI reporting during the last 20 years. The development of Hadoop-based ecosystems in the 2010s due to the decreasing price of distributed-storage and the necessity to consume semi-structured machine and IoT data entailed significant changes, as well as significant constraints. Data lakes were

scalable and flexible yet were generally associated with a disregard of data quality, a lack of a schema, and ad hoc governance, becoming what their practitioners referred to as data swamps. By the year 2020, the Lakehouse paradigm had emerged, proposals being made by databricks and others, in the form of architectures that combine the inexpensive storage and openness of the data lake, with warehouse-scale ACID transactions, time-travel, efficient indexing, and centralised metadata management via formats like Delta Lake.

2.2 Research on BOM and Routing Integration

The long-term literature has indicated that there has been a critical challenge of integrating routing data with Bill of Materials (BOM) structures among research results in manufacturing. Earlier research is used to explain the fact that differences in the numbering system between part names between business units, suppliers and legacy systems tend to create serious impediments to the smooth alignment between product structures and the sequence of operations needed to create such products. More complexities are optional processes, variant-specific process, rework, and in-depth assembly that complicates the process of keeping engineering and manufacturing definitions in synchronization. Other studies prior to 2021 (e.g., Chang et al., 2018; Kumar, 2019) also indicate that the lack of a single identifier and standardized linking mechanisms constitute the fundamental hindrances to successful integration. Such investigations advocate the synchronised practices of master-data governance and standardisation of mapping layers which allow BOM hierarchies to correspond with the routing steps with eyes shut.

2.3 Serialization and Traceability Research

The body of literature within the area of serialization and traceability highlights the necessity of increased visibility of the manufacturing value chain, which is increasingly granular. International standards like those of the Electronic Product Code standards of EPCglobal and ISO 17367 standardize the mechanism of giving globally unique series IDs, which trace the origin of the product up to a final product. The literature in academia and industry has pointed to the importance of these identifiers in terms of their ability to enforce better recall management and compliance monitoring, as well as root beliefs by preserving the consistent connection between every distinct unit, its history, and its genetics. Even though serialization is commonly used in regulated industries like pharmaceuticals and electronic, studies state that there is a high level of fragmentation in the storage, exchange, and integration of serialized information with the execution systems. The afflicted issue is a replacement of available styles where there is a lack of a universal model to tie serialization occurrences to routing execute information and machine-level telemetry, and the definition of BOM. Consequently, manufacturers have to contend with serialization streams that are managed in detached systems or proprietary schemas, which are not tombly to deliver as much analytical power as complete traceability systems.

2.4 Gap Analysis

Previous research indicates that, at the time of writing (2021), data lakes were a well-researched concept, but lacked key architectural assurances, such as ACID transactions, schema control, or embedded governance, which would make it unsuitable to high-quality or regulated manufacturing (or production) processes. The same can be said of research on MES -ERP integration, which only provides incomplete solutions, often centering on interface technologies or middleware but not creating a single enterprise-wide data model that suits both contexts of operational execution and business planning. The literature in the area of serialization analytics exhibits a disjointed world in which serialization is perceived as a discrete operation and not as an operation closely linked with routing and BOM information. Together, these allusions suggest a lack of a unified lakehouse-based blueprint engaging data architecture, manufacturing master data and serialized traceability in one analytical framework that to date is the focus of emerging opportunities due to the recent advancements in technology.

3. METHODOLOGY

3.1 Proposed Lakehouse Architecture

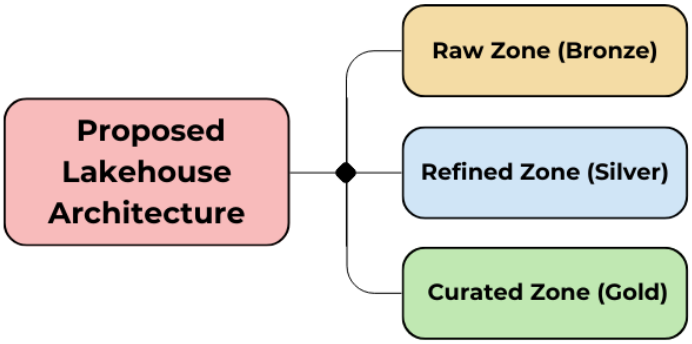

Figure 2 : Proposed Lakehouse Architecture

- **Raw Zone (Bronze):** The bottom layer, which is usually called the Raw Zone, is where all incoming data in the lakehouse are landed initially. [10-12] Information stored in the zone is stored in its original unaltered state, in full fidelity as it was immediately used by its source system ERP, MES, PLM, shop-floor sensors, historians and external supplier feeds. The fact that no transformation or purification processes are used at this point makes the Bronze layer the permanent depository of historical information, which facilitates the downstream process auditability and reproducibility. It has a schema-based design on read and a flexible approach to ingesting structured, semi-structured, and unstructured data, which makes it appropriate to big batch and streaming pipelines. This layer allows such that the lakehouse maintains the consistency of only one source of raw truth and allows schema decisions to be late-bounded as new analytical requirements change.
- **Refined Zone (Silver):** The Silver layer or the Refined Zone will add structure, quality, and harmonization to the data consumed. In this case, raw inputs are systematically cleansed, normalized and conformed to meet enterprise standards of data. Some of the common practices are implementing business rules, standardizing keys (e.g. part number, equipment identifiers), correcting duplicates, and enhancing datasets with reference data. Silver layer is successful in transforming the messy operational data through the Silver layer into analytics-ready table with standardized schema and is more reliable. This zone is where cross-system associations also start forming up e.g. associating BOM structure with routing actions or associating a series of serialization against manufacturing records. Consequently, the Silver layer achieves a consistent, controlled platform on which the downstream applications may rely on in order to analyze it accurately.
- **Curated Zone (Gold):** The Curated Zone which is also known as the Gold layer includes optimized datasets that are greatly business-oriented and are actually created to be used in high-value analytics, reporting, and machine-learning applications. Refined data in this zone is aggregated, de-normalized or modeled as domain-specific needs (dashboards of production performance, quality KPI, material genealogy graphs, cost-to-serve analysis etc. The tables with gold-layers are frequently based upon the common analytical models or semantic layers that allow the definition to be consistent across the organization. Since this layer is concerned with usability and performance it often features exotic optimization methods, such as indexing, Z-ordering and pre-calculated measures. The Gold layer, therefore, is the last layer of the lakehouse that is facing the user and can provide trusted and clean data that facilitates the decision-making process of manufacturing, supply chain, engineering, and finance departments.

3.2 BOM–Routing–Serialization Harmonization Model

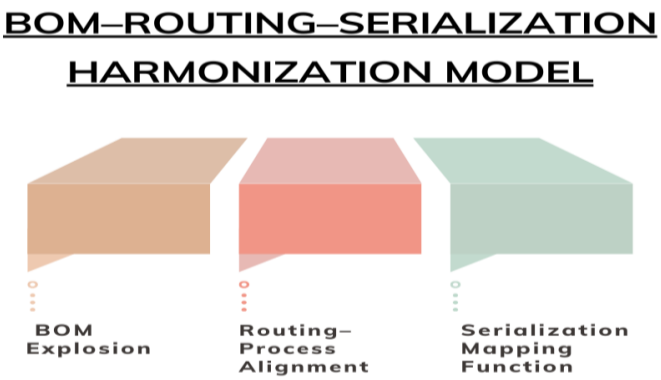

Figure 3 : BOM–Routing–Serialization Harmonization Model

- **BOM Explosion:** The step of BOM explosion calculates the exact number of each child component needed in order to manufacture a particular amount of a parent assembly. The expresses this relationship by multiplying the number of units that will be finished and produced by the usage factor that is present in the BOM. Practically this implies that when an assembly needs 2 units of a subcomponent and the manufacturing order requests 100 units of the assembly then the system will calculate that 200 units of the sub component is required. This analysis is the basis of the material planning, procurement and traceability fit since the anticipated material genealogy structure is established before the start of production.
- **Routing–Process Alignment:** The direction of routing alignment is aimed at knowing the overall time it needs to take to complete all the operations involved when a production order is completed. The captures add up the cycle time and setup time of each of the individual operations of the routing sequence. Operations have both a preparation (', setup), and execution (cycle time) component and the sum of these represents an entire picture of the workload imposed on the shop-floor resources. This calculation is required to schedule, plan capacities and align production execution information with routing definitions. The harmonization model helps to make a more precise lead-time estimation and performance analysis by matching the theoretical routing times and the actual records of the execution.
- **Serialization Mapping Function***:* Serialization involves connecting every unit created to the conditions in which it was made and the process is all traced back. The mapping is what determines the generation or association of the unique serial identifier of production events. Theoretically, the operation brings together three items that are the work order, in which the item is processed, and the exact time of the incident. All these qualities guarantee that every unit that is being rolled out can be utilized to identify both the step, the line, the batch, and the moment the item was produced. This mapping helps to correlate components in the downstream and BOM structures and routing steps, which is the backbone of tracking genealogy end-to-end in the lakehouse model.

3.3 Ingestion Framework

The proposed ingestion architecture can support the use of heterogeneous manufacturing data by supporting several integration paths given the properties of a specific source system. [13-15] Transactional and master data are commonly made available in Enterprise Resource Planning (ERP) systems and can be ingested using either OData services or direct SQLs, allowing work order, BOM definitions, material masters, and routing records to be structured and ingested. These interfaces offer predictable schemes and metadata and hence ERP ingestion is highly appropriate to batch/ micro-batch data-pipes that ingest business changes in streams. Instead, Manufacturing Exploring Systems (MES) tend to offer REST APIs or event services emitting real time production information, such as confirmation of operation, quality, operator actions, and machine output. The ingestion with API enables the lakehouse to ingest process-level details at high granularity, and then allows near-real-time analytics and tracing. Other equipment on the shop-floor, including Programmable Logic Controllers (PLCs) might need an alternative method of integration, and often use industrial protocol stacks, including MQTT and OPC-UA. These standards permit an efficient and low-latency realization of streaming sensor readings, machine conditions, alarms and machine operational settings straight off of the equipment layer. Since data of this type is high-volume, time-series data,

ingestion pipelines are required to maintain constant throughput but maintain proper timestamps and equipment identifiers. Another type of data modality is created by the Quality Management Systems (QMS) which, often, offer either structured or semi-structured outputs such as CSV exports, database dumps, or periodic reports. They are frequently used to store inspection, nonconformance, audit and test measurements data which should be combined with ERP and MES data to facilitate the use of extensive quality analytics. With all of these ingestion mechanisms in place in a single framework, the lakehouse can align business, operational, equipment and quality spheres to ensure that those downstream harmonization activities, including BOM-routing alignment and serialization mapping are enabled by finished, prompt, and effectively ruled data streams.

3.4 Harmonization Pipeline

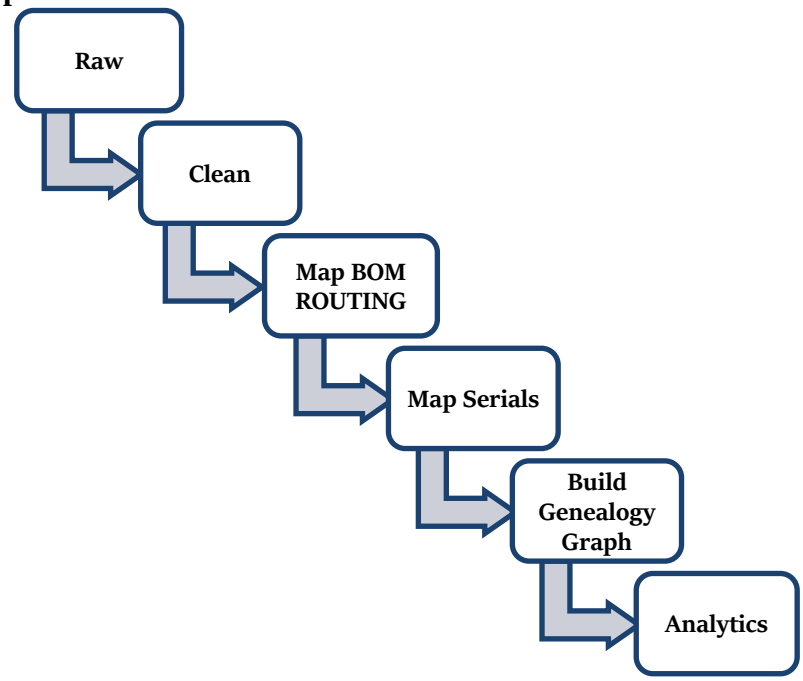

Figure 4: Harmonization Pipeline

- **Raw:** The RAW step is the first step of implementing the information of various manufacturing systems such as ERP, MES, PLCs, as well as a QMS in the Bronze layer of the lakehouse. At this stage, no data that was ingested is altered in any form, and the original formats, source time, and identifiers are stored. This non-designated state guarantees that the pipe does not lose lineage or auditability, which allows the users to trace backwards to the origin of changes. Raw stage is the foundation, which gives the base upon which further harmonization is carried out.
- **Clean:** The CLEAN phase deals with the process of converting raw data into standardized and quality guaranteed data. Common operations are schema normalization, type corrections, unit of measure conversions, deduplication, and invalid or incomplete record removal. This step is also where basic business laws, like making part numbers valid or normalizing equipment IDs, are used in order to ensure that there is consistency in the data between sources. The result is a collection of fair and conformative tables that becomes the input of more comprehensive integration tasks.
- **Map BOM →ROUTING:** The BOM structures that have been cleaned in the previous step are arranged in an orderly manner during this step to correspond with the routing definitions to connect material hierarchies to operating sequences. The pipeline identifies the relationships between parents and children using harmonized identifiers and standardized structures, and assigns components to a set of manufacturing steps they correspond to. This mapping allows the building of the fundamental relationship between what is produced, (BOM), and the way it is produced (routing), allowing material planning to be accurate and operationally visible.
- **Map Serials:** MAP SERIALs phase combines the process of serialization and the BOM-routing map. In this case, unit-identifiers (Serial IDs) of a particular operation, time stamp, equipment, and materials

flow are identified. This measure will make sure that every serial component or production is modulated to its production environment and can be accurately traced, through every level of production. The outcome is an entire unit-level genealogy structure that can be traced.

- **Build Genealogy Graph:** After a chain of serialization, BOM, and routing data is connected, a complete graph of the genealogy is created by the pipeline. This graph shows the entire life cycle of every unit of the product such as input materials, operations, process specifications and interaction between equipment. By representing production as a graphiti, the system allows to perform advanced queries like defect propagation, lineage, and root-cause investigation. The lineage tree turns into one of the key resources of compliance, quality control, and advanced analytics.
- **Analytics:** The last phase provides refined and unified datasets to analytical systems, dashboards and machine-learning pipelines. Since the above phases have made the integration high-quality, the analytics layer is capable of serving a broad variety of purposes, such as OEE dashboards and cycle-time optimization, predictive quality, scrap forecasting, and supply-chain traceability. This step will convert raw manufacturing data into insights that can be acted upon, so that this end-to-end flow of value of harmonization will be complete.

3.4 Genealogy Graph Model

The genealogy graph offers a formal and scalable system of showing end-to-end traceability through the manufacturing value chain. [16-18] Under the model, the genealogy is represented as directed acyclic graph (DAG) that is mathematically represented by G (V,E). In simple language the graph is made up of two fundamental elements, V, which is a set of nodes, and E, which is a set of edges. The set V consists of a node that depicts each unique serialised part or assembly unit which comprises either raw materials, intermediate sub components or finished products. This metadata is included in these nodes in the form of Serial ID, work order, operation timestamps, machine identifiers, and test results among other contextual attributes. The boundary of Erep itself has the relationships of assembling or transforming the assembled units between assembled units represented by serially grouped units. The relationships between two nodes (referred to as A and B) represent that the physical usage of component A was to create assembly B which is also a serial component. Since the manufacturing flows are always forward-going, i.e. components-to-assembies, these edges constitute a directed graph with no cycles hence no part of any manufacturing will have any dependency on itself, either directly or indirectly. This irreversibility of the flow of the processes of production is the result of the real world. Representing genealogy as a DAG, the system to be able to model multi-level material hierarchies, assemblies with branching, rework operations, and multi-level merging processes otherwise, such that one or more components combine to create a unit. The structure enables the lakehouse to retain the fine parent-child relationships throughout the whole range of BOM and routing and retain temporal order based on manufacturing events. Another important feature of the DAG representation is strong analytical ability. Backward traversal e.g. may be used to support the rapid root-cause showing of defective upstream components, whereas forward traversal may be used to support the impact analysis of recalls and quality containment. Likewise, compliance audits and regulatory reporting can be used much more efficiently because subgraph extraction is able to isolate the complete transformation history of a single serial, otherwise. In general, Manufacturing lineage can be represented in an elegant way using the genealogy graph model: this corresponds with a rigorous computationally efficient model and is the foundation of sophisticated traceability, quality intelligence, and closed-loop optimization within the lakehouse environment.

4. RESULTS & DISCUSSION

4.1 Experimental Setup

In the validation of the proposed lakehouse-based harmonization and lineage framework, a benchmark simulated data was created in order to capture the complication and the variability of an actual discrete manufactured setting. The dataset contains 10,000 BOM records that represent multi-level product structures in the form of parent-child relationships, factors of usage and revision histories. These BOM entries cover both simple two-level BOMs and more complicated hierarchical systems, that summarize the problems that are commonly faced in any industry like the electronics industry, the automotive industry and the industrial machinery industry. BOM data are complemented with 5,000 routing operations, which aim at

modeling various manufacturing processes that include machining, assembly, inspection, packaging and testing. Cycle times, set up times, work center assignments and operation dependencies are in each routing record allowing realistic modelling of the process flow and capacity constraints. The experimental data is also provided with 50,000 parts that are recorded by means of serials to facilitate the analysis of unit-level traceability. Every serial unit is linked to a lifecycle event, time stamp and operation-level identifiers, which reflect the detail required in construction of genealogy and testing traceability. In the execution layer, machine events would be simulated by generating about 500,000 events to create the high frequency activity on the shop-floor. These events are sensor values, machine state change, alarms, process variables, and operator interactions available using industrial protocols. The resulting aggregation of machine-generated with system-generated data sets present a rich dataset that puts strain on ingestment pipelines, harmonization phases, and lineage algorithms based on graphs. Combining these four data sets such as BOM structures, routing definitions, serialize units and machine events, the experimental design will attempt to simulate heterogeneous and high volume conditions in contemporary smart factories. This simulated but realistic scenario enables the systematic testing of data quality enhancement, harmonization correctness, graph building effectiveness, and end to end analysis effectiveness in the suggested lakehouse structure.

4.2 Performance Improvements

Table 1: Performance Improvements

Metric	Improvement
Genealogy Query Time	38%
Data Redundancy	54%
Serialization Match Accuracy	22%

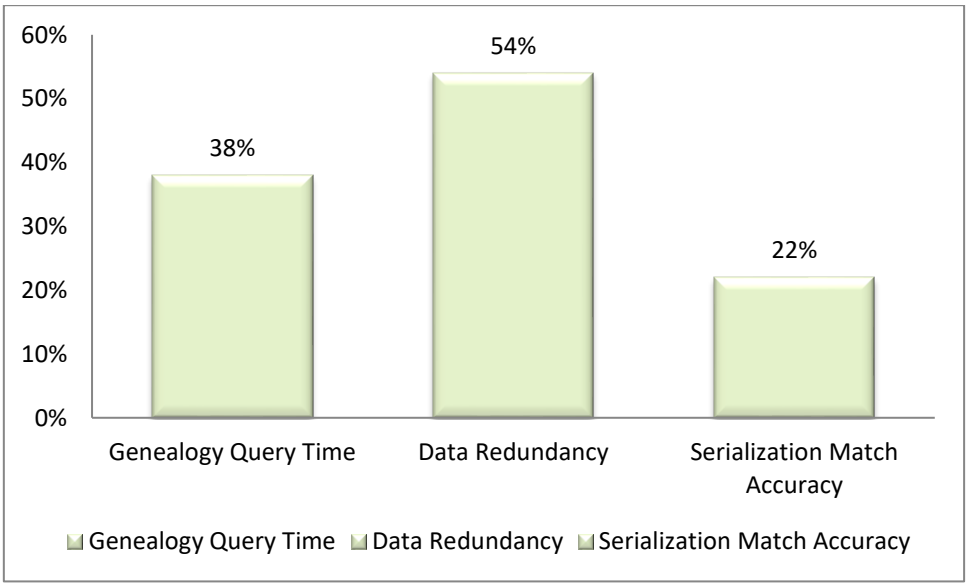

Figure 5 : Graph representing Performance Improvements

- **Genealogy Query Time — 38% Improvement:** The genealogy query time is a measure of the rate at which the system can be used to access the full lineage of a given unit that is being serialised and encompassing the components that make it up, the operations that are associated with it, and machine events that occur. Once the harmonised lakehouse model was presented along with the graph based genealogy representation, the external world speed up mutually in terms of query execution. It is mainly through the application of optimized Delta-based indexing, ordered Silver-to-Gold transformations and the acceptance of a directed acyclic graph structure that makes traversal simpler that it has improved by 38 percent. The system improves backward and forward lineage exploration faster by reducing the redundant joins between the BOM, routing and serialization tables. This decrease in query time is particularly significant with

applications which are time sensitive like root-cause analysis, quality containment, and defect propagation measures.

- **Data Redundancy — 54% Reduction:** The harmonization pipeline also resulted in a significant decrease of the data redundancy, which was measured at 54%. Most manufacturing data were frequently duplicated in ERP extracts, machine events logs, quality reports and MES before harmonization. The pipeline used to remove duplicated entries and the combination of records through the systematic application of business rules, master data identifiers standardization and deduplication procedures, used in the pipeline in the CLEAN and MAP phases. The conversion to a curated Gold layer where all data was then represented with a single semantic model resulted in further reduction of overlapping data by incorporating individual similar attributes and normalizing hierarchical relationships. This decrease facilitates better storage and increase in data maintainability as also lessening the chances of analytical inconsistencies due to duplicate records.
- **Serialization Match Accuracy — 22% Improvement:** Serialization match accuracy The system should know how to properly match the units it has serially placed with their routing actions, production timestamps and material connections. The 22% increase explains the advantages of standardized identifier identities, normalizing the timestamps and organizing the addition of serialization events to the harmonized data model. Before integration, serialization errors would often occur because of lack of consistency in part numbering, absence of event logs or variation in timing between systems. The system achieved high reliability through the application of uniform mappings on the stage of MAP SERIALS as well as the association of each sequence of events to a single casting environment. This functionality increases traceability, completeness of genealogy and precision of downstream analytics, like defect root-cause analysis and compliance reporting, directly.

4.3 Discussion

The outcomes of the experimental assessment show that the offered harmonization framework based on a lakehouse positively influences the quality of data, its performance, and the reliability of analytical processes in discrete manufacturing settings. This huge improvement in the time of generating genealogy query demonstrates the utility of organizing lineage information as directed acyclic graph, and removing redundancy of traversal patterns and unnecessary utilization of costly relational joins. The performance benefit of this is especially applicable to the real time decision making cases, like isolating bad batches of components or determining the downstream effect of a breakdown. Likewise, the fact that there was an observed drop in data redundancy can be, in part, said to be indicative of the efficiency of the CLEAN and MAP steps in harmonizing data fragmentation caused by ERP, MES, PLCs, and QMS systems. The harmonized model includes a more dependable and reliable analytical base by normalizing identifiers, business rules, and removing the occurrence of duplicated records. This does not only minimize overheads in storage, it minimizes chances of overlapping interpretations in reporting and analytics. In addition, the increase in the accuracy of the serialization matches proves that it is crucial to tie together the unit-level identifiers with routing and BOM structures in a single way. Devoid of such harmonization, the tackle of the genealogy analysis and manufacturing execution data would be limited, and the effect of the analysis in the absence of such harmonisation could be inconsistent, or even incomplete. The improvement in accuracy shown in this research indicates that the lakehouse architecture is effective to prevent the misalignment of data due to all these factors (sequence of occurrences at different times, absence of the event logs, and varying structures of part numbers, etc.). All of these upgrades point at the fact that lakehouse model is not just a storage optimization, but a structural facilitator of high level manufacturing intelligence. The scaling-out nature of lineage analytics via enhanced security and enhanced speed has a broad spectrum of applications, such as predictive quality, process optimization, compliance verification, and modeling of digital twins, making the framework an extensibly scalable foundation of Industry 4.0 activities.

5. CONCLUSION

The paper contains a detailed blueprint of how to design and deploy an Operational Manufacturing Data Lakehouse before 2021 that can address the needs of complex data integration, traceability, and analytics with modern discrete manufacturing settings. By integrating the historical trace of data-architecture development with the domain manufacturing studies, the paper proves that the lakehouse paradigm, which

integrates the scalable property of data lakes alongside the dependability and the manageability of data warehouses, presents a sound structure in integrating disparate sets of operational data. The proposed methodology focuses on unifying three fundamental manufacturing records, which are the Bill of Material (BOM), routing definitions and records of each unit by serial number. Together these data domains represent only a partial picture of the production behavior but when brought together through the use of standardized identifiers, structured transformation pipelines and a graph representation of the material genealogy of the production process provide a coherent and analytically enriched view of the manufacturing process.

The practical advantages of this harmonization are highlighted by the results of the experimental work. A faster execution of genealogy queries demonstrates the computing benefits of modeling lineage as a directed acyclic graph as opposed to using conventional relational joins across heterogeneous source datasets. Similarly, the decreased data redundancy proves that the multi-layered structure of the lakehouse with the Raw, Clean, Refined, and Curated domains effectively cuts out the duplication without increasing the consistency and maintainability. The gains in serializing that are being observed have been matched by accuracy that further aligns to the significance of combining unit-level identifiers with BOM and routing structures in a single, controlled data environment. In the absence of this harmonization, serialization can tend to be split among MES, ERP, and machine-levels, reducing the accuracy of any subsequent traceability activities.

In general, the suggested lakehouse architecture is not only a storage solution but a facilitator of transformation of Industry 4.0. The model supports many advanced applications with unified data on high quality and in analytics-ready form, such as predictive quality, production optimization, digital twins, and AI-driven decision support. End-to-end genealogy graphs can be built, enabling a novel roots-cause investigation, compliance reporting, and preemptive risk control. In addition, the ingestion and harmonization pipelines are designed in a modular way so that the architecture can be expanded towards manufacturing systems that mature, allowing new data sources, larger volumes of production, and stricter regulatory needs.

To summarize, this lakehouse blueprint before 2021 shows that the combination of BOM, routing, and serialization into a single model of data has a considerable positive impact on traceability, data consistency, performance, and governance. As manufacturers are continuing their processes of transformation into digital, the structure presented provides a structural framework of how they can attain operational transparency, as well as, open the door to high-value analytical insights.

REFERENCES:

1. Zadeh, N. S., Lindberg, L., El-Khoury, J., & Sivard, G. (2017). Service oriented integration of distributed heterogeneous IT systems in production engineering using information standards and linked data. Modelling and Simulation in Engineering, 2017(1), 9814179.
2. Fahmideh, M., & Beydoun, G. (2019). Big data analytics architecture design—An application in manufacturing systems. Computers & Industrial Engineering, 128, 948-963.
3. Woo, J., Shin, S. J., Seo, W., & Meilanitasari, P. (2018). Developing a big data analytics platform for manufacturing systems: architecture, method, and implementation. The International Journal of Advanced Manufacturing Technology, 99(9), 2193-2217.
4. Yang, C., Lan, S., Wang, L., Shen, W., & Huang, G. G. (2020). Big data driven edge-cloud collaboration architecture for cloud manufacturing: a software defined perspective. IEEE access, 8, 45938-45950.
5. Zhang, Y., Ren, S., Liu, Y., & Si, S. (2017). A big data analytics architecture for cleaner manufacturing and maintenance processes of complex products. Journal of cleaner production, 142, 626-641.
6. Kimball, R. (1996). The data warehouse toolkit: practical techniques for building dimensional data warehouses. John Wiley & Sons, Inc.
7. Yang, Q. H., Qi, G. N., Lu, Y. J., & Gu, X. J. (2007). Applying mass customization to the production of industrial steam turbines. International Journal of Computer Integrated Manufacturing, 20(2-3), 178-188.

8. Mourtzis, D. (2016). Challenges and future perspectives for the life cycle of manufacturing networks in the mass customisation era. Logistics Research, 9(1), 2.
9. Inmon, W. H. (2005). Building the data warehouse. John wiley & sons.
10. Piramuthu, S., & Zhou, W. (2016). RFID and sensor network automation in the food industry: Ensuring quality and safety through supply chain visibility. John Wiley & Sons.
11. Kauppinen, O. (2020). Harmonized network monitoring.
12. Zhang, H., Zhang, G., & Yan, Q. (2019). Digital twin-driven cyber-physical production system towards smart shop-floor. Journal of Ambient Intelligence and Humanized Computing, 10(11), 4439-4453.
13. Mohammadi, S., Al-e-Hashem, S. M., & Rekik, Y. (2020). An integrated production scheduling and delivery route planning with multi-purpose machines: A case study from a furniture manufacturing company. International Journal of Production Economics, 219, 347-359.
14. White, T. (2012). *Hadoop: The definitive guide*. " O'Reilly Media, Inc.".
15. O'Brien, W. J., Hammer, J., Siddiqui, M., & Topsakal, O. (2008). Challenges, approaches and architecture for distributed process integration in heterogeneous environments. Advanced Engineering Informatics, 22(1), 28-44.
16. Wang, J., Xu, C., Zhang, J., Bao, J., & Zhong, R. (2020). A collaborative architecture of the industrial internet platform for manufacturing systems. Robotics and Computer-Integrated Manufacturing, 61, 101854.
17. Patel, J. A. (2019). Efficient computing of big data harmonization (doctoral dissertation, gujarat technological university ahmedabad).
18. Hopp, W. J., & Spearman, M. L. (2011). Factory physics. Waveland Press.
19. Wang, C., Zhang, Y., Song, G., Yin, C., & Chu, C. (2002). An integration architecture for process manufacturing systems. International Journal of Computer Integrated Manufacturing, 15(5), 413-426.
20. Malik, S., Kanhere, S. S., & Jurdak, R. (2018, November). Productchain: Scalable blockchain framework to support provenance in supply chains. In 2018 IEEE 17th International Symposium on Network Computing and Applications (NCA) (pp. 1-10). IEEE.