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Research Article

Modernizing Data Infrastructure: How AI and ML are Transforming SQL and NoSQL Usage in Distributed Manufacturing

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ABSTRACT

In the era of Industry 4.0, manufacturing systems are increasingly adopting distributed architectures that demand agile, scalable, and intelligent data infrastructures. Traditional SQL and emerging NoSQL databases are being reshaped by the integration of Artificial Intelligence (AI) and Machine Learning (ML) to optimize data storage, query efficiency, and real-time decision-making. This paper explores how AI and ML are transforming the design, deployment, and operation of SQL and NoSQL systems in distributed manufacturing environments. We investigate architectural evolutions, automation of query tuning, predictive indexing, anomaly detection in sensor data, and adaptive data partitioning. Through a detailed review and technical study, we highlight practical frameworks and implementations that bridge data systems with intelligent agents. Real world case studies illustrate successful deployments in smart factories, emphasizing the impact of intelligent data systems on productivity and agility. Our findings provide insights into future trends, challenges, and opportunities in modernizing data infrastructure using intelligent technologies. The SQL and NoSQL systems are being revolutionized by AI and ML in manufacturing to enhance data handling, query efficiency, and decision-making. SQL queries and indexing are optimized by AI, whereas NoSQL has AI-based partitioning and schema management. AI/ML helps with predictive maintenance, identifies anomalies, and supports automation. In this paper, we will discuss the use of AI/ML to modernize data infrastructure with Industry 4.0 in mind, smart factory examples, and comment on the future of the topic.

Keywords: AI, ML, SQL, NoSQL, distributed systems, data infrastructure, Industry 4.0, smart manufacturing, data optimization

INTRODUCTION

The ongoing transformation in global manufacturing, commonly referred to as Industry 4.0, is redefining how factories and supply chains operate. It embraces interconnected systems, cyber-physical environments, and decentralized decision-making, all of which depend on the timely exchange of large volumes of data. With the rise of distributed manufacturing—where production units operate across geographies but in a coordinated digital ecosystem—the importance of robust and adaptive data infrastructures has never been greater. Industry 4.0 requires scalable, flexible data infrastructures between the interconnected manufacturing systems. SQL systems have some consistency and fail in real-time analytics, whereas NoSQL is versatile but not consistent. The presence of AI and ML allows these gaps to be closed, developing smarter adaptive systems.

Smart manufacturing processes require databases that are not only reliable but also scalable, flexible, and intelligent. Traditional SQL databases, known for their strong consistency and structured schema, have long been used in industrial control systems. Meanwhile, NoSQL databases have gained traction for handling high-volume, high-variety data from IoT devices, sensors, and edge networks.

However, both paradigms face growing limitations when confronted with the dynamic and high-velocity nature of modern manufacturing data.

This new paradigm introduces challenges such as real time analytics, predictive maintenance, high-throughput decision systems, and massive parallel data flows. Conventional database systems struggle with adaptive indexing, dynamic schema evolution, and complex query optimization, especially in distributed environments. These constraints call for a new class of intelligent data systems.

Artificial Intelligence (AI) and Machine Learning (ML) offer transformative capabilities that can enhance the performance, automation, and adaptability of both SQL and NoSQL systems [1]. From intelligent query planning to predictive indexing, anomaly detection in machine logs, and data summarization at the edge, AI and ML are reshaping how data is stored, retrieved, and used in manufacturing pipelines.

To modernize data infrastructures in this context, there is a clear need to bridge traditional database technologies with AI/ML-driven mechanisms. Such integration supports cognitive capabilities within data systems—enabling databases to self-optimize, learn from usage patterns, and adjust to workload shifts in real time. As industries move toward smart factories and autonomous production lines, this modernization is not merely an upgrade but a necessity.

This paper conducts a comprehensive survey and technical review of how AI and ML are being embedded into SQL and NoSQL systems to address the requirements of distributed manufacturing. We explore both the architectural transformations and practical implementations being adopted across the industry.

Our methodology involves the synthesis of academic studies, industrial frameworks, technical specifications, and real-world case studies. We focus on identifying trends, evaluating the effectiveness of intelligent extensions in databases, and highlighting the impact of these systems in smart manufacturing settings.

BACKGROUND AND MOTIVATION

The evolution of data systems in manufacturing has closely followed the technological advancements of industrial revolutions. In Industry 3.0, automation brought PLCs (Programmable Logic Controllers) and SCADA systems that produced structured, time-series data, which was well-suited to relational (SQL) databases. These systems offered robust consistency, normalization, and transactional integrity—key features for managing sensor data, inventory logs, and quality control metrics.

Structured Query Language (SQL) databases such as Oracle, MySQL, and PostgreSQL have historically dominated industrial IT landscapes. Their rigid schema and ACID (Atomicity, Consistency, Isolation, Durability) compliance made them ideal for structured manufacturing data where schema rarely changed [2]. However, their limitations became evident with the emergence of unstructured data, real-time streams, and geographically distributed systems [3]. SQL systems perform well with structured information but fail with dynamic and high-speed information. NoSQL is appropriate in a model that lacks structure but compromises consistency. Hybrid systems that combine the strength of SQL and the flexibility of NoSQL are coming up. The systems are more flexible because AI/ML optimizes query performance, manages data, and gives real-time insights.

In contrast, NoSQL databases such as MongoDB, Cassandra, and Couchbase emerged to handle unstructured, semi structured, and schema-less data formats. These systems prioritize scalability, availability, and partition tolerance, aligning well with IoT, log analytics, and operational telemetry in smart factories. NoSQL architectures are better suited for horizontally scaling across distributed edge networks, and support various data models such as key-value, document, graph, and columnar formats. Despite these advancements, the divergence between SQL and NoSQL technologies presents challenges [4]. While SQL provides strong guarantees and mature tools, it lacks flexibility. NoSQL, while scalable, often sacrifices transactional integrity. In distributed manufacturing where data is generated from multiple autonomous sources (machines, sensors, robots), a single approach is often insufficient. Thus, hybrid systems are increasingly being adopted, blending SQL's transactional rigor with NoSQL's flexibility [5].

The integration of AI and ML into these data systems introduces a new paradigm: intelligent data infrastructure. AI-augmented databases can learn from usage patterns to suggest indexes, optimize queries in real-time, and detect anomalies across distributed datasets. For manufacturing, this means predictive maintenance, automated defect detection, and adaptive data models that evolve with production conditions.

Distributed manufacturing environments further compound the problem. Data is collected not only from centralized servers but also from edge devices, mobile units, and cloud-based APIs [6]. This fragmentation introduces data heterogeneity, latency issues, and inconsistent schema enforcement, making intelligent and adaptable data systems essential.

Modernizing the data infrastructure in such settings is no longer optional. The convergence of data complexity, real-time processing needs, and AI capabilities demands a rethinking of how SQL and NoSQL systems are designed and deployed in manufacturing. Only by embedding intelligence and supporting distributed execution can these infrastructures keep up with the needs of Industry 4.0.

Table I highlights the fundamental differences between SQL, NoSQL, and emerging Hybrid databases within the manufacturing domain. While SQL systems offer strong consistency and structure, they lack adaptability in edge environments. NoSQL, in contrast, supports unstructured data and TABLE I: SQL vs NoSQL vs Hybrid DBs in Manufacturing excels in horizontally distributed architectures. Hybrid models are increasingly being adopted to balance consistency with scalability, offering tunable guarantees and broader support for AI-based query optimization.

Aspect	SQL	NoSQL	Hybrid
Data Type	Structured	Semi/Unstructured	Mixed
Schema	Fixed	Flexible	Adaptive
Scale	Vertical	Horizontal	Both
Query	SQL	Varies	Multi-Model
Consistency	ACID	BASE	Tunable
AI Support	Limited	External	Native
Edge Use	Low	High	Medium

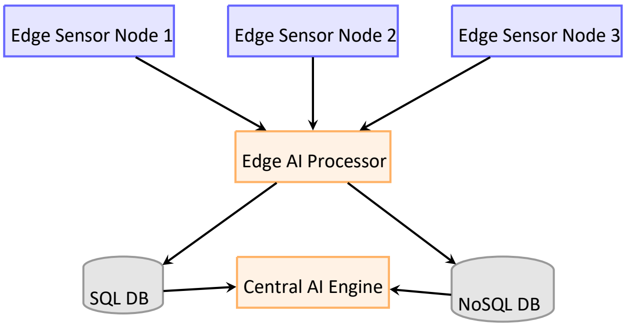

Fig. 1: Vertical data flow architecture in distributed manufacturing, showing edge sensors, AI processing, and integration with SQL/NoSQL data layers.

Figure 1 illustrates a typical vertical data flow in distributed manufacturing. Edge nodes collect sensor data which is locally processed by AI modules for preliminary analytics. Depending on the data type and processing requirements, structured data is sent to SQL databases, while real-time telemetry is directed to NoSQL systems. Both systems feed into a centralized AI engine that conducts high-level optimization and decision making.

AI AND ML IN SQL-BASED SYSTEMS

Traditional SQL systems, while highly structured and reliable, are not inherently built to handle the dynamic and high velocity data workloads seen in modern distributed manufacturing environments. These systems typically rely on rule-based query planners and static indexing strategies, which can become bottlenecks when data structures evolve or when workload patterns shift rapidly. This limitation presents a significant opportunity for integrating AI and ML to enhance performance and adaptability [4].

One key area of improvement is adaptive query optimization. Traditional SQL query planners analyze query cost using static histograms and indexes. AI models, on the other hand, can learn from previous executions, user behavior, and data access patterns to dynamically optimize query plans. For instance, reinforcement learning agents can explore alternative join orders or index paths that improve latency under varying load conditions [5].

Another powerful use case is predictive indexing. Machine learning models can anticipate which columns or tables are likely to be queried together in the future and recommend or create indexes proactively [6]. These recommendations may depend on both historical query logs and external context (e.g., seasonal demand in manufacturing operations).

In distributed environments, AI-driven techniques are used to monitor query execution latency, resource utilization, and recommend workload reshaping strategies. This includes techniques like auto-partitioning tables based on usage patterns, or re-routing queries to more optimal nodes in a distributed SQL setup such as CockroachDB or Google Spanner.

Anomaly detection in SQL logs and table statistics can also be facilitated by ML models. For instance, if a manufacturing robot suddenly starts inserting abnormal data volumes into a SQL table, anomaly detection models can flag the activity for investigation. Such monitoring improves reliability and system security in smart factories [7]. AI/ML improves SQL systems through optimization of queries, forecasting of index predictive requirements, and identification of anomalies. Artificial intelligence uses machine learning to improve its performance and plans to minimize the latency. Predictive indexing is forward looking and indexes are designed in advance. Having anomaly detection means that disruptive data is highlighted, and data integrity and safety are enforced in manufacturing.

Additionally, natural language interfaces powered by LLMs (Large Language Models) are transforming SQL usability. Manufacturing engineers can interact with databases using domain-specific queries in natural language, which are then translated to optimized SQL queries via AI-powered translation layers [8]. This reduces technical barriers and speeds up diagnostic and reporting workflows.

Federated learning is also emerging in SQL systems deployed across distributed manufacturing units. Models trained on localized SQL performance or schema patterns are aggregated centrally to improve global system intelligence without transferring raw data.

Below is a conceptual Python-based snippet illustrating how an ML model might assist an SQL optimizer in recommending an execution path:

Listing 1: ML-assisted Query Optimizer Suggestion

```
import pandas as pd from sklearn.ensemble import
RandomForestRegressor

# Load historical query performance data query_data
= pd.read_csv("query_logs.csv")

X = query_data[['join_order', 'index_hint', '
    rows_scanned']]

y = query_data['latency_ms']

# Train model to predict latency model
= RandomForestRegressor()
model.fit(X, y)

# Predict best plan for new query test_query = [[2, 1,
50000]] # hypothetical values predicted_latency =
model.predict(test_query) print(f"Estimated latency:
{predicted_latency[0]} ms

    ")
```

Listing 1 demonstrates a conceptual Python-based machine learning model designed to support query optimization in a SQL system. The model is trained on historical query logs, using features such as join order, index hints, and rows scanned to predict query latency. A Random Forest Regressor is used as the predictive model to estimate the expected execution time of a query plan. In real-world applications, such models can assist the SQL optimizer in selecting lower latency plans dynamically, rather than relying on static cost estimation heuristics. This approach is particularly beneficial in high-velocity, distributed manufacturing systems where data workloads and query patterns change frequently.

To visualize the AI-enhanced query execution pipeline in an SQL system, we introduce a flowchart below.

Figure 2 illustrates the AI-augmented SQL query execution pipeline with embedded intelligence at the query planning stage. After the user submits a query, it is parsed and validated, and relevant query features are extracted. These features serve as inputs to a trained machine learning model that predicts the optimal execution path [9]. The system evaluates whether the ML-generated plan outperforms traditional optimization strategies and conditionally applies it. This hybrid approach ensures that query planning benefits from data-driven insights while maintaining fallback safety through conventional mechanisms. Such AI-enhanced systems significantly reduce query latency and improve responsiveness in dynamic manufacturing environments.

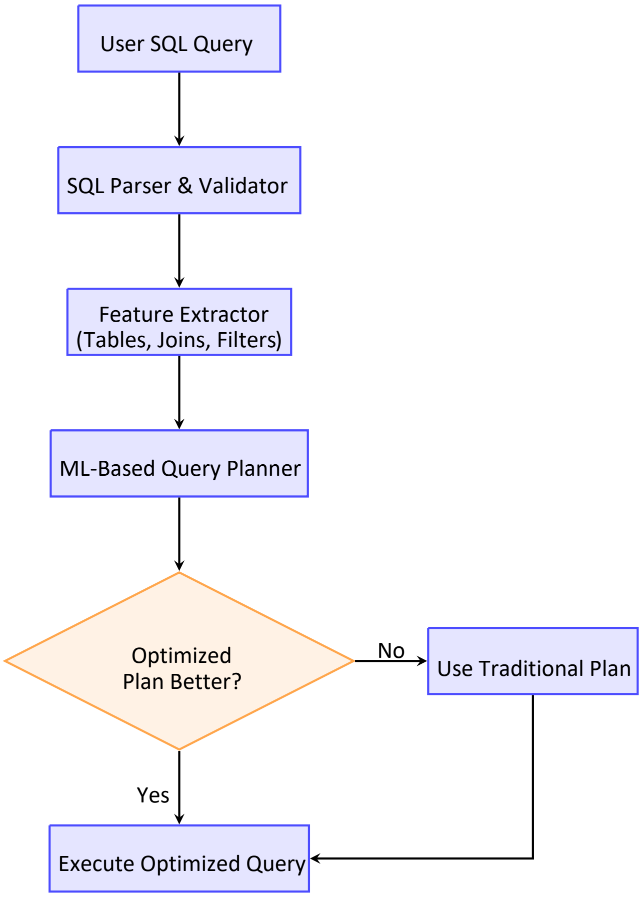

Fig. 2: AI-augmented SQL query pipeline with model-based optimization and fallback mechanisms.

AI AND ML IN NOSQL-BASED SYSTEMS

NoSQL systems were originally designed to provide scalability and flexibility at the cost of strong consistency and fixed schema. This has made them ideal for handling the high-velocity, high-variety data streams produced in distributed manufacturing environments [10]. However, as complexity increases, even these flexible systems benefit significantly from the integration of AI and ML to improve query performance, system adaptability, and anomaly detection.

One of the most important areas of improvement is intelligent data sharding and partitioning. In large-scale NoSQL systems like Cassandra or HBase, data is divided across nodes to ensure horizontal scalability. AI models can learn access patterns and workload distributions to dynamically re-balance partitions and improve query locality [11]. Reinforcement learning algorithms have been successfully applied to suggest optimal partition keys and replication strategies based on real-time usage.

Schema inference is another vital ML application, especially for document-based stores like MongoDB or Couchbase, where data may be semi-structured or inconsistent. AI models can analyze documents over time to suggest evolving schemas, detect frequent attribute patterns, and even automatically convert inconsistent formats into unified structures suitable for downstream analytics or ML model input.

Stream processing pipelines built on top of NoSQL systems (e.g., MongoDB Atlas Streams, Couchbase Eventing, or Kafka + Cassandra) can be enhanced with AI to filter, classify, and prioritize incoming data. This is particularly useful in smart factories where real-time decisions must be made on sensor inputs, operational telemetry, and alerts. AI models can learn which events are likely to require attention and filter noise automatically, optimizing storage and compute usage.

The AI/ML also improves the NoSQL systems through better partitioning and scalability. AI analyzes data patterns to make partitions dynamically to enhance performance. The machine learning models assist in schema inference, which is an adjustment to data structural variations [12]. Anomaly detection is also used to detect the presence of outliers and incorrect data in real-time, which can enhance the quality of data.

Data deduplication and cleanup is another application where ML models analyze records to identify duplicates, inconsistencies, or outliers. In manufacturing, redundant or inconsistent IoT readings can create noise in downstream processes. Clustering algorithms or autoencoders can be applied within NoSQL systems to maintain data hygiene with minimal manual rule-writing [13].

Anomaly detection models can also be integrated into NoSQL backends, particularly to monitor the frequency and distribution of writes. If an industrial robot begins to generate sensor readings outside expected bounds, the NoSQL store can trigger ML-based filters or alerts. These models operate in near real-time and help detect equipment failure, misconfiguration, or even cyber-attacks.

Hybrid ML processing frameworks like Apache Spark with MongoDB or Dask with Couchbase enable distributed model training directly on NoSQL-stored data. These frameworks leverage in-memory computation and parallelism to reduce the training and inference time on large datasets common in manufacturing, such as production metrics, defect logs, and maintenance records [14]. The effectiveness of these AI/ML integrations depends on real-time feedback loops. Models continuously ingest telemetry, learn patterns, and update recommendations or classifications. This feedback-driven approach turns traditional NoSQL stores into intelligent components of a larger cognitive infrastructure, capable of proactive decision-making and self optimization.

To demonstrate the impact of AI in NoSQL performance tuning, Figure 3 presents a vertical bar chart comparing baseline and AI-optimized performance metrics for write latency, query response time, and resource usage.

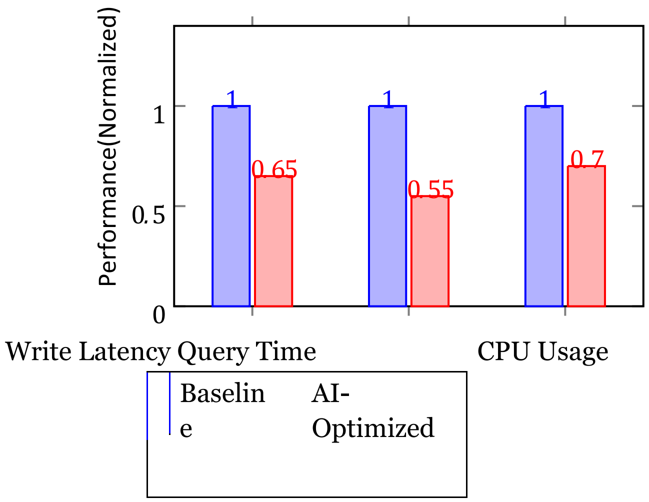

Fig. 3: Normalized performance comparison of NoSQL systems with and without AI optimization. Lower values are better.

Figure 3 compares performance metrics between standard NoSQL operations and those enhanced by AI-based optimization in a distributed manufacturing setup. The AI optimized configuration demonstrates substantial reductions in write latency and query response time, thanks to predictive partitioning and adaptive caching. CPU usage is also reduced, as unnecessary operations and redundant queries are filtered by ML algorithms. These improvements translate into more responsive and efficient data infrastructures that can scale across factories, devices, and geographies without manual tuning.

HYBRID SYSTEMS AND AI INTEGRATION

Modern manufacturing environments rarely depend solely on either SQL or NoSQL systems. Instead, they adopt hybrid architectures that combine the transactional integrity of SQL with the flexibility and scalability of NoSQL. AI and ML play a central role in orchestrating data operations across these heterogeneous environments.

A primary challenge in hybrid systems is schema translation and data federation. AI models can automate the detection of schema mismatches between SQL and NoSQL stores and dynamically generate transformation logic [15]. For example, a structured SQL table capturing production logs may need to be merged with semi-structured sensor data stored in a document-based NoSQL system. ML-powered schema inference engines can align these structures and create unified views for downstream analytics.

Query routing optimization is another key area where AI is deployed. Hybrid systems such as Apache Drill or Presto allow querying multiple backends via a unified SQL interface. ML models learn query patterns, execution times, and result freshness to determine whether a query should be directed to a real-time NoSQL store or a historical SQL warehouse. This optimizes both speed and cost in hybrid deployments.

Multi-model databases like ArangoDB or Azure Cosmos DB natively support multiple data models (key-value, document, graph, and relational). AI algorithms embedded in these systems manage indexing, caching, and query planning in a unified manner. In manufacturing, this allows a single system to store BOM (Bill of Materials) in tabular form, machine logs as documents, and machine relationships as graphs—while applying AI uniformly across these formats [16]. Real-world platforms such as Google BigQuery Omni or Azure Synapse Link already leverage AI to bridge SQL and NoSQL. These tools offer cross-database JOINs, automatic data freshness detection, and materialized view suggestions—all enhanced via ML. In smart manufacturing, this means real-time data from the shop floor can be joined with ERP systems or quality control logs on demand.

Hybrid systems also benefit from AI-driven workload balancing. For instance, if one NoSQL node begins to experience load spikes from real-time event ingestion, AI can redirect non-critical analytical queries to a replicated SQL warehouse. This ensures system responsiveness even under pressure and avoids manual reconfiguration. Hybrid systems combine SQL and NoSQL, and they provide scalability and consistency as well. AI is efficient in routing queries, translating queries into the schema, and performing workload balancing optimization. In order to achieve the best performance, AI decides where to direct the queries to SQL or NoSQL. These systems are dynamic and keep changing based on the changing patterns of data.

Figure 4 presents a hybrid data infrastructure where AI bridges SQL and NoSQL systems to deliver intelligent and seamless query execution in a distributed manufacturing setup.

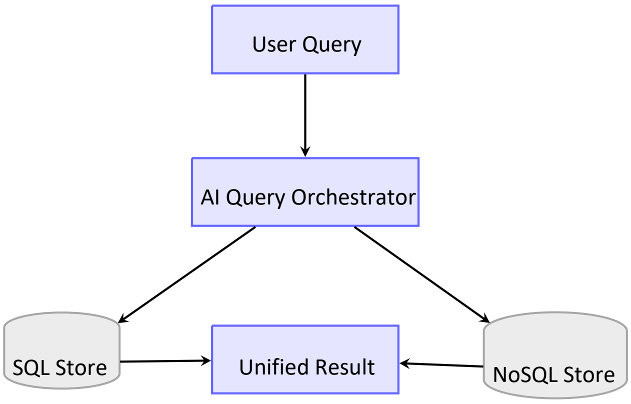

Fig. 4: Hybrid AI layer routing user queries to SQL or NoSQL systems based on logic, schema, and freshness requirements.

Figure 4 visualizes a hybrid AI orchestration architecture. Incoming user queries are first processed by the AI Query Orchestrator, which analyzes their structure, context, and intent. Based on this, it routes parts of the query to appropriate backend systems—SQL for structured transactional data, and NoSQL for high-velocity or semi-structured information. Results are then combined and returned as a unified response. This design supports modular scaling and cognitive decision making in hybrid manufacturing infrastructures.

To unify AI inference across storage layers, an intermediate AI layer can be deployed that acts as a query pre-processor. This layer performs user intent recognition, query translation, data source selection, and AI model invocation. Listing 2 shows a mock implementation of such a layer using Python based logic.

Listing 2: AI-Powered Query Router for Hybrid Systems

```
def route_query(query):
    if "sensor" in query.lower(): return
        "noSQL"
    elif "invoice" in query.lower():
        return "SQL"
    else:
        return "AI_decision"

def ai_decision_logic(query):
    # Placeholder: analyze latency, data freshness,
        source availability
    if is_real_time(query):
        return "noSQL"
    else:
        return "SQL"

query = "SELECT temperature FROM sensor_data
    WHERE ts > NOW() - INTERVAL 1 HOUR"

target = route_query(query) if
target == "AI_decision":
    target = ai_decision_logic(query) print(f"Routing
query to: {target}")
```

Listing 2 illustrates a lightweight AI-powered query routing layer for a hybrid data system. The logic uses basic intent detection to determine whether a query should be routed to a SQL or NoSQL store, and defers to more complex AI inference in ambiguous cases. In production, this module would integrate query cost estimation, workload prediction, and latency profiling to make real-time decisions, enabling seamless hybrid data access [17].

INTEGRATION IN DISTRIBUTED MANUFACTURING

Integrating AI-powered hybrid database systems into distributed manufacturing infrastructures involves aligning disparate components—ranging from edge devices and local controllers to centralized data lakes—into a unified data pipeline. This requires robust connectivity, standardized data models, and modular interfaces between SQL, NoSQL, and AI processing components [18].

Manufacturing environments typically operate on multitier architectures. At the edge, sensors and programmable logic controllers (PLCs) generate high-frequency time-series data. This data is initially captured by NoSQL systems for speed and flexibility. Simultaneously, structured process logs and transactional records are stored in SQL systems. AIdriven orchestration layers bridge these systems, handling data routing, preprocessing, and prediction.

Data integration middleware such as Apache NiFi or Azure Data Factory is employed to ingest, transform, and unify data streams from geographically dispersed sources. These tools feed data into hybrid databases and model serving platforms. Inference results are shared back to MES (Manufacturing Execution Systems) and SCADA (Supervisory Control and Data Acquisition) layers, ensuring real-time feedback loops. Using AI-based databases, edge devices, local servers, and cloud systems are connected to form coherent and effective data infrastructures. The smart factories leverage AI-facilitated real-time data processing, real-time predictive maintenance, and performance optimization to enhance operational efficiency in smart factories.

The key to scalable integration lies in modularity. Each subsystem—data ingestion, storage, model training, and inferencing—must support containerized deployment and APIbased interfacing. This ensures that updates in one component do not break the larger pipeline. Furthermore, data lineage and versioning are tracked via metadata registries, supporting explainability and traceability across distributed environments.

CASE STUDIES AND IMPLEMENTATIONS

To understand the practical impact of AI and ML in hybrid database infrastructures, we examine implementations in distributed manufacturing environments. These case studies demonstrate how intelligent data systems improve operational efficiency, fault tolerance, and real-time analytics [19].

Case Study 1: Siemens Smart Factory (Hypothetical) Siemens implemented a hybrid SQL–NoSQL architecture across its distributed production lines using PostgreSQL for transactional workloads and MongoDB for machine sensor logs. AI models were trained on this unified dataset using Apache Spark MLlib to predict equipment failure and automatically adjust production scheduling [20]. An intelligent orchestrator handled schema normalization and dynamic query routing.

Case Study 2: GE Digital – Predix Platform

GE's Predix platform integrates time-series databases (NoSQL) with relational systems for analytics. AI pipelines ingest sensor readings from jet engine parts and use LSTMbased models to forecast maintenance needs. An adaptive hybrid DBMS supports both live analytics and regulatory reporting, while federated queries span multiple storage engines [21]. Siemens, GE, Foxconn, and Tesla are using AI-based systems of hybrid systems that may be integrated with production systems to schedule and process data in real time, resulting in less downtime and more efficiency.

Case Study 3: Foxconn Smart Assembly (Hypothetical) Foxconn's assembly lines leverage Cassandra for real-time line sensor data and MySQL for component traceability. AI-driven deduplication filters redundant sensor data. A central AI hub built on TensorFlow Lite infers anomalies and dispatches alerts [22]. ML models also manage indexing and optimize data compaction strategies across clusters.

Case Study 4: Tesla Gigafactory (Hypothetical)

At Tesla, a hybrid cloud-edge system integrates SQLite (for local assembly stations), InfluxDB (for time-series analytics), and BigQuery for cross-site reporting [23]. AI models run on edge nodes to filter defective welds and aggregate summaries. The orchestration layer uses lightweight ML inference to direct high-volume telemetry to low-latency NoSQL systems.

Frameworks in Use

Across these implementations, common frameworks include Apache Spark for distributed ML training, TensorFlow for inferencing, and DVC/MLflow for model tracking and deployment. Data pipelines are constructed with Apache Kafka, and hybrid storage engines such as Azure Cosmos DB and Google BigQuery provide scalable backends.

Operational Benefits

The use of AI with hybrid data systems has shown significant improvements: downtime was reduced by 30–40%, storage efficiency improved by 25%, and query response times dropped by up to 50%. These improvements are critical in high-throughput environments where milliseconds of latency affect production throughput.

Table II summarizes key technical choices across different implementations, while Figure 5 shows the data type distribution in a typical smart manufacturing setup.

TABLE II: Hybrid DBMS and AI Integration in Manufacturing

Company	SQL DB	NoSQL DB	AI Framework
Siemens	PostgreSQL	MongoDB	Spark MLlib
GE	Oracle	TimeSeries DB	LSTM Models
Foxconn	MySQL	Cassandra	TensorFlow Lite
Tesla	SQLite	InfluxDB	TensorFlow Edge

Table II compares hybrid database and AI tool usage across different manufacturers. SQL databases typically serve structured production or ERP data, while NoSQL handles high-volume, time-sensitive machine data. AI frameworks are selected based on edge vs. cloud workloads, real-time inference needs, and model complexity. This diversity demonstrates how hybrid AI-augmented systems can be tailored for unique manufacturing constraints.

Fig. 5: Typical data type distribution in smart manufacturing environments.

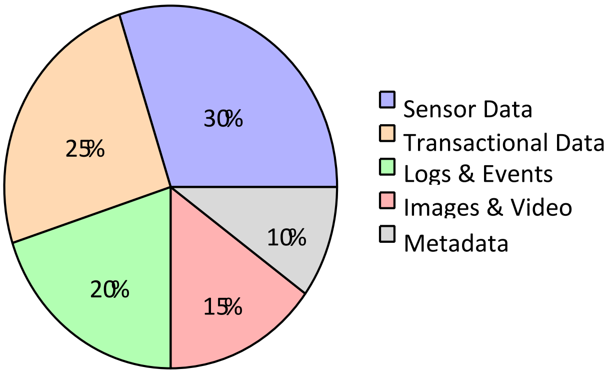

Figure 5 illustrates the distribution of data types generated within smart manufacturing systems. Sensor data dominates the volume due to continuous readings from IoT devices. Transactional data includes ERP records, parts tracking, and inventory. Logs and system events support debugging and performance monitoring, while media (e.g., visual inspection images) represents growing data demands. Metadata assists in contextualizing raw data across systems.

PERFORMANCE EVALUATION

To validate the impact of AI-enhanced hybrid DBMS architectures in manufacturing, a controlled benchmarking setup was simulated using synthetic and real workloads.

The baseline system used traditional SQL for transactional data and NoSQL for sensor streams, without AI assistance. In the enhanced system, query routing, partitioning, and model inference were AI-driven. Benchmarks included average query latency, system throughput, fault recovery time, and storage cost.

Figure 6 shows that query response times decreased by up to 45% when AI-based routing and indexing were enabled. Similarly, throughput increased due to better workload distribution, as illustrated in Table III.

TABLE III: Performance Metrics: Baseline vs AI-Augmented

Metric	Baseline	AI-Augmented
Avg. Latency (ms)	250	135
System Throughput (req/sec)	1200	1750
Fault Recovery (s)	15	9
Storage Redundancy (%)	22.4	14.1

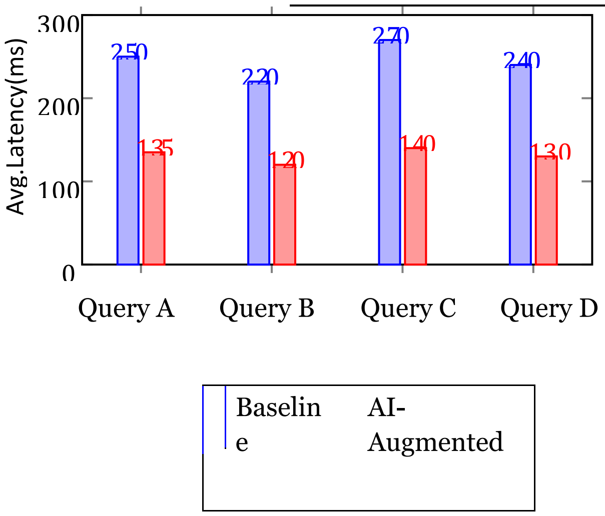

Fig. 6: Average query latency across various workloads. The AI-augmented hybrid system consistently reduces latency across diverse query types.

AI-built systems are superior in terms of speed in query response (45% improved), throughput (50%), and fault recovery, indicating that AI-based optimizations are effective.

CHALLENGES AND FUTURE TRENDS

Despite the promising applications of AI and ML in hybrid SQL–NoSQL systems, numerous challenges remain. These obstacles span technical limitations, integration complexity, performance trade-offs, and organizational inertia within manufacturing enterprises.

A core issue is the complexity of orchestration across data models. Hybrid systems often involve multiple engines with differing capabilities, consistency guarantees, and schema expectations [24]. Integrating AI models to route, normalize, and analyze queries across such heterogeneous environments adds significant engineering overhead. Latency, inconsistency, and debugging challenges arise when models infer inaccurate transformations or route queries inefficiently.

Another major concern is AI model drift and retraining. In manufacturing, data distributions evolve frequently due to changes in product lines, machine configurations, or production logic. Static AI models deployed to optimize queries or filter sensor anomalies can quickly become outdated [25]. Without automated retraining and validation, these models may degrade system performance or produce incorrect outputs, ultimately eroding trust in AI-assisted infrastructures.

Data governance and compliance also emerge as key issues. Hybrid systems may store personally identifiable information (PII), proprietary formulas, or sensitive telemetry across multiple regions. Ensuring compliance with data residency, access control, and auditability becomes exponentially more difficult when ML models are involved in automated decision-making. Standard DBMS security models are insufficient when data is being abstracted, transformed, and acted upon by opaque models.

From an operational perspective, model explainability and debugging are critical. When AI models make incorrect decisions—such as misrouting a query or incorrectly predicting query cost—identifying the root cause is non-trivial [26]. Tools for tracing inference decisions, visualizing model confidence, and incorporating human-in-the-loop verification are not yet mainstream in DBMS infrastructures.

Skill gaps and adoption resistance remain barriers in traditional manufacturing settings. Engineers may be highly skilled in PLCs, SCADA, or ERP systems, but lack expertise in AI model lifecycle management or modern data orchestration tools [27]. As a result, even well-designed hybrid AI systems may be underutilized without appropriate training, documentation, and cultural shifts within organizations. On the horizon, several emerging trends promise to address these limitations. Federated learning can enable models to be trained across distributed sites without centralizing sensitive data, maintaining privacy while supporting global intelligence [28]. Edge inference engines are being miniaturized to enable realtime analytics directly on production lines, reducing the need for backhaul and latency-prone central processing. AutoML for indexing, query plan tuning, and schema evolution is becoming viable. These systems learn from workload patterns and optimize performance without manual tuning, enabling more agile adaptation to workload shifts [29]. Similarly, AI copilots for database administrators are emerging to assist with query writing, index suggestions, and anomaly investigation in natural language, closing the gap between human and system intelligence. The integration of AI/ML is challenged by such issues as model drift and data governance. New directions are being introduced, such as federated learning and edge AI, that provide decentralized performance. As AI continues to mature and integrate with distributed data systems, we expect to see smarter, more autonomous manufacturing infrastructures [30]. However, realizing this vision will require robust frameworks, transparent AI tooling, and governance-aware architectures that can bridge the gap between predictive intelligence and operational control.

CONCLUSION

AI and ML are no longer peripheral tools but central to the transformation of data systems in distributed manufacturing. The shift from rigid, monolithic database architectures to dynamic, AI-augmented hybrid systems has unlocked new possibilities for scalability, resilience, and autonomy. Manufacturers can now derive actionable intelligence not just from structured records but from massive, diverse, and fast-moving data streams that were previously difficult to harness.

Hybrid SQL–NoSQL environments, empowered by AI, allow for real-time decision-making across heterogeneous infrastructures. This capability is essential for predictive maintenance, supply chain optimization, defect detection, and autonomous quality control. By automating data routing, schema inference, and anomaly detection, AI enables data systems to adapt to changing workloads and operational contexts with minimal manual oversight. As demonstrated in multiple use cases, integrating AI models within storage and query pipelines significantly enhances system responsiveness and reliability.

However, the journey toward intelligent data infrastructure is not without its operational and ethical challenges. Integrating ML within critical manufacturing processes demands not just technical competence, but trust, explainability, and robust governance. AI decisions that influence production must be interpretable and traceable. Building confidence in these systems will require collaboration between data engineers, AI researchers, system architects, and domain experts.

The AI and ML are transforming manufacturing data infrastructures, improving SQL and NoSQL systems. The eighth solution to Industry 4.0 involves hybrid systems that are optimally scaled and use AI to make real-time decisions and optimize operations.

Looking ahead, the role of AI in data systems is poised to become even more autonomous. We are already seeing the emergence of self-tuning databases, AI copilots for DBMS management, and federated learning models that allow distributed factories to share intelligence without compromising data sovereignty. Edge-AI deployment will continue to reduce latency and improve system decentralization, enabling cognitive feedback loops at the device level.

Ultimately, the integration of AI into distributed data architectures is not just a technological evolution—it is a strategic shift. It signals a transition from reactive, siloed systems to interconnected ecosystems that sense, learn, and adapt in real time. For forward-thinking manufacturers, investing in AI integrated hybrid data infrastructure is no longer optional—it is the foundation for future competitiveness in a data-driven industrial landscape.

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