Manufacturing Analytics System: A New IT Category Enabling Next-Level Operational Excellence

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Manufacturing Analytics System: A New IT Category Enabling Next-Level Operational Excellence

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Abstract: The manufacturing sector is undergoing a substantial digital transformation. Following decades of developments in data capture technologies, computer science, and IT infrastructure, manufacturers collect and store more data than ever. However, collecting data is one challenge; another is using it. Many manufacturers are struggling to take advantage of the possibilities offered by advanced analytics. This paper introduces a new category of industrial IT system that solves this problem: the Manufacturing Analytics System (MAS).

Keywords: Manufacturing Analytics System, Artificial Intelligence, Digital Transformation, Industry 4.0, Cyber-Physical Production System.

1. INTRODUCTION

Rapid developments in digital technologies have enabled manufacturers to collect and store a wide range of data from their operations (Kusiak 2017, Kusiak 2018). Progress in data capture technologies, the standardization of communication protocols, and the emergence of cloud-based storage and computational capabilities are critical enablers (Lee et al. 2015, Monostori et al. 2016). However, manufacturers often struggle to realize the latent productivity potential in their data resources (Olsen and Tomlin 2020). Consequently, data is underutilized in driving operational improvements (Corbett 2019). Beyond stand-alone software packages for specific use cases, such as predictive maintenance or process mining, there is a void of integrated analytics software that helps realize the promise of cyber-physical production systems or "Industry 4.0" at scale.

Despite considerable investments in digitization, the application of analytical tools in manufacturing is still limited (Lorenz et al. 2022). Manufacturers face a situation characterized by an abundance of data but a scarcity of actionable information. They are "data rich but information poor." For example, IBM reports that around 90% of industrial sensor data is never analyzed.[1] This issue arises from several factors: data being stored in separate sources, fragmentation and verticalization of software, loss of contextual metadata, and a lack of standardization across sites, equipment, Information Technology (IT), and Operational Technology (OT). As a result, operations managers, process experts, and data engineers face significant challenges in aggregating, cleansing, wrangling, and using data. This calls for unifying analytical standards and workflows to utilize existing data effectively.

In response to these challenges, this paper proposes a new category of IT: the Manufacturing Analytics System (MAS). A MAS is designed to create a unified context for disparate data sources, employ custom artificial intelligence (AI) models for data analysis, and deliver insights through a suite of interoperable applications. These applications can be customized for various user types involved in improving operational processes. A MAS acts as an intermediary between data and users, offering data-driven insights rapidly. It enables the automation of data analysis and information presentation, facilitating better decision-making in manufacturing.

The paper is structured as follows. Section 2 reviews the literature on IT/OT interoperability and manufacturing analytics. Section 3 introduces the MAS as a suggested solution to enable more integrated and effective analytics in manufacturing. In Section 4, the capabilities of the MAS are highlighted via three common use cases: root cause analysis, chat-based data exploration, and process monitoring to enhance operational efficiency. Section 5 provides a short conclusion.

2. BACKGROUND

Two streams of research are particularly relevant to this paper: (1) the literature on IT/OT interoperability and (2) the emerging literature on manufacturing analytics.

2.1 IT/OT Interoperability

In recent years, much progress has been made in developing IT/OT systems and facilitating their interoperability and integration. According to Baudin and Netland (2022, p. 289), OT refers to industrial computer-based systems that "drive, monitor, and respond to machines, robots, conveyor systems, or vehicles," and IT refers to those that "only exchange data with other systems or with people." Together, IT/OT infrastructure is an infrastructural backbone for collecting and forwarding the data required to apply advanced analytics in manufacturing.

[1] See IBM article at https://www.ibm.com/blogs/southeast-europe/cognitive-manufacturing-industry-4-0/ (last accessed on January 29, 2024).

The rapid developments of OT, such as modern machine controllers, sensors, auto-ID, and other data capture technologies, have lowered the barrier to collecting more and more types of data, in higher frequencies than before. This data can be transmitted to IT systems, which have seen a sharp rise in increased capacity and flexibility due to the emergence of cloud computing (Monostori et al. 2016). Overall, there is clear evidence that increasing amounts of detailed data are being collected and made more readily available (Kusiak 2017, Kusiak 2018).

Recent IT/OT advances have contributed to manufacturing efficiency gains, but the potential is much more significant. This motivates seeking to overcome two remaining hurdles. On the one hand, there are infrastructural hurdles, such as those described by Pennekamp et al. (2023): scalable processing of data in motion and at rest, device interoperability, data security and data quality, network security, and infrastructure for secure industrial collaboration. And on the other hand, there is an active search for architectural solutions and the establishment of best practices. Lee et al. (2015) describe the remaining practical hurdles and the proposal of a five-layer architecture from data collection and connection to the configuration of supervisory controls of production machines.

2.2 Manufacturing Analytics

Modern factories generate vast amounts of data, which can be used to generate insights for productivity improvement (Kusiak 2017). This data spans the production value chain, including process models, order information, operational histories, raw material data, environmental data, product measurements, process measurements, quality data, and images. Manufacturing analytics is essential for capturing the full value of these data assets (Wuest et al. 2016, Kusiak 2018, Tao et al. 2018, Lorenz et al. 2022). Several applications of manufacturing analytics already exist. Among the most prominent are quality management, production planning, and maintenance (cf. Senoner 2021).

First, *quality management* has emerged as one of the key areas of research on manufacturing analytics. Reported applications are quality inspection (Bergmann et al. 2019, Chen et al. 2020), root cause analysis (Chen et al. 2005, Chien et al. 2007, Senoner et al. 2022), and quality prediction (Wu & Zhang 2010, Lieber et al. 2013). Second, manufacturing analytics is used in *production planning*. For example, manufacturing analytics has been used for scheduling (Waschneck et al. 2018, Kuhnle et al. 2019, Senoner et al. 2023), predicting lead times (Lingitz et al. 2018, Gyulai et al. 2018), and managing production capacity (Gyulai et al. 2014, Schneckenreither et al. 2021). A third key focus area of manufacturing analytics is *maintenance*. There are numerous applications reported for remaining-useful-life estimation (Ren et al. 2017, Sun et al. 2019), fault classification (Susto et al. 2015, Wang et al. 2020), and condition monitoring (Luo et al. 2019, Michau et al. 2020, Michau et al. 2022).

Other promising application areas in manufacturing include process parameter optimization (Pfrommer et al. 2018), bottleneck detection (Subramaniyan et al. 2020), and energy management (Lu et al. 2020)—in addition to office tasks like purchasing, human resource management, and engineering support. This paper contributes to the literature on manufacturing analytics by proposing and defining an IT system that enables these applications to be used more holistically and effectively.

3. PROPOSED SYSTEM ARCHITECTURE

A MAS provides interoperable end-user applications that address the numerous challenges manufacturers are faced with in pursuit of operational excellence. These challenges look different on the factory floor, upper management levels, and between. However, the interoperability requirement means avoiding siloed solutions is necessary. The proposed MAS architecture addresses this via a shared core of AI models, which are then used in problem-specific ways by the MAS applications. The models must also be decoupled from the various mechanisms required to deal with the variety of data sources and data quality in modern manufacturing.

In response to these challenges, this paper proposes a three-layered MAS architecture:

- an *Application Layer* with user-facing software addressing specific manufacturing needs,
- a *Model Layer* with AI models specialized for manufacturing challenges, and
- a *Context Layer* pulling in various data sources and representing their relationships.

Figure 1 illustrates this MAS architecture and how it bridges the gaps between data sources and end-users. The following subsections describe each layer in more detail.

3.1 Context Layer

The Context Layer serves as the foundation of a MAS. It prepares and organizes the data for its use in the Model Layer. This layer does not duplicate existing databases. Instead, it stores only relevant data, automatically wrangled together from different sources in a unified and aggregated format. It provides a crucial link across disparate data sources. This is achieved by mapping or creating common identifiers like timestamps, part IDs, and batch IDs. The context and connections in this layer enable comprehensive analysis across different datasets.

3.2 Model Layer

The Model Layer comprises advanced AI models for complex data analysis in manufacturing. Unlike standard data platforms that use off-the-shelf machine learning algorithms (e.g., Random Forests, CNNs, etc.), this layer involves tailored AI models specifically designed for manufacturing tasks (e.g., root cause analysis, visual inspection, material flow analysis, etc.). Tailored models in this layer enable a MAS to effectively address context-specific challenges where generic approaches are of limited use.

3.3 Application Layer

The Application Layer contains the user-facing applications that leverage the data processed by the underlying layers. Due to the shared architecture of the models in the Model Layer, the results from one application can be passed on to others for further processing or aggregation, for example, to create integrated reports or configurable operational user-centered dashboards. It also becomes feasible to build frameworks for no-code applications. Users engage with the relevant information in tools that are custom-built for manufacturing workflows. The applications can be both interoperable and fine-tuned for intuitive use by each user type and problem type that matters for operational excellence in the firm-specific manufacturing context.

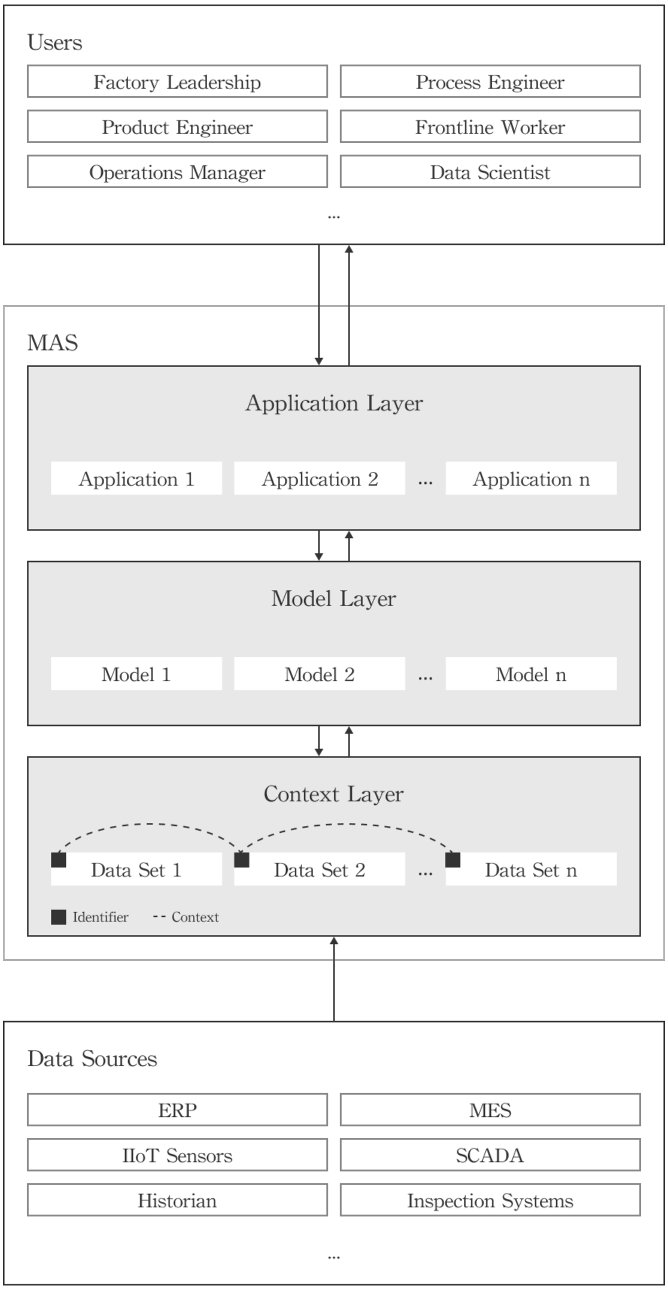

Figure 1. The three layers of a Manufacturing Analytics System (MAS) make the varying and disparate data available to AI models, whose insights are then presented in applications tailored to the needs of specific end-users involved in the improvement of production.

4. USE CASES

This section describes three exemplary use cases of the MAS: (1) root cause analysis, (2) chat-based data exploration, and (3) process monitoring. All use cases are based on real-life implementation of MAS in industry-leading companies.

4.1 Root Cause Analysis

Root cause analysis is a systematic process to identify the underlying causes of production issues. For this purpose, manufacturers increasingly rely on data-driven methods to investigate undesirable production outcomes such as quality losses, downtime, and high energy consumption. These issues often have varied and complex origins, necessitating data analysis from multiple data sources (e.g., MES and Historian). A root cause analysis in MAS can be realized as follows:

- The Context Layer is responsible for mapping independent variables (e.g., process parameters like temperature and pressure) and dependent variables (e.g., quality or downtime) into a unified data format that can be analyzed. This standardization is needed so that the models in the Model Layer can assess how different parameters influence production outcomes.
- The Model Layer contains custom models for root cause analysis (e.g., Chen et al. 2005, Chien et al. 2007, Senoner et al. 2022). These models are different from applying off-the-shelf machine learning (e.g., assessing feature importance based on predictive models like Random Forests). For example, Senoner et al. (2022) developed a data-driven decision model that is specifically designed to identify sources of quality variation and subsequently select suitable actions for quality improvement.
- The Application Layer is where the outputs of the Model Layer are translated into actionable insights. It uses data visualization techniques to present how various parameters are interrelated, enabling domain experts to design physical experiments or implement improvements in their production lines.

4.2 Chat-Based Data Search

Chat-based data exploration with Large Language Models (LLMs) is a novel approach for interacting with and analyzing vast data sets. Users describe in natural language what information they want to retrieve (e.g., "What was the average quality on this production line in January 2024?"), and custom LLMs are used to respond to these queries. Here, the MAS serves as an intermediary between the user and the data.

- The Context Layer stores the contextualized production data and makes it accessible to the LLM in the Model Layer. It ensures this data is in a format that the LLM can access, understand, and analyze effectively.
- The Model Layer can be based on open-source LLMs like LLaMa 2 (Touvron et al. 2023) or Mistral (Jiang et al. 2023). These models can be specifically fine-tuned to handle manufacturing queries based on the predefined data format. Fine-tuning enables the LLM to produce better results because generic models may lack the domain-

specific knowledge required for manufacturing. When the LLM receives a prompt via the Application Layer, it executes a custom code function to extract the requested insights from the contextualized data in the Context Layer.

- The Application Layer is essential for bidirectional communication in the system. It serves as the interface through which users send queries to the Model Layer and receive the requested insights.

4.3 Process Monitoring

Detailed monitoring and tracking of production processes is difficult with traditional methods such as statistical process control. These methods struggle to handle the large heterogeneity of data modern factories generate. Machine learning models are well suited to monitor high-dimensional production data and detect anomalies. In this context, the MAS ensures that models can monitor data across the entire value stream.

- The Context Layer is responsible for collecting and aggregating high-dimensional production data. For example, it matches time series data from different machines into an aggregated format with the same timestamp granularity. The data is then pre-processed in a way that it can be interpreted by the monitoring models in the Model Layer.
- The Model Layer incorporates machine learning models that are designed to monitor high-dimensional production data. Examples include unsupervised model architectures (e.g., Michau et al. 2020, Michau et al. 2022) that can determine whether a parameter or a combination of parameters behave differently from a predefined baseline.
- The Application Layer displays process behaviors in real-time. It alerts users about potential anomalies and suggests troubleshooting actions before a process gets out of control.

5. CONCLUSIONS

Over the past decades, manufacturers have considerably improved their data acquisition capabilities (Lee et al. 2015, Monostori et al. 2016, Kusiak 2017, Baudin and Netland 2022). However, to benefit from their data assets, manufacturers need advanced analytics that can access and analyze data stored in disparate formats and sources. This paper proposes the MAS as the solution to this problem.

The proposed MAS is a new IT system category. It enables more effective analytics across different use cases by unifying diverse data sources and employing tailored AI models. It overcomes challenges related to the interoperability of models, applications, and data and integrates tightly into user workflows. Overall, the MAS offers manufacturers access to advanced analytical capabilities and user-centric applications to improve operational decision-making in pursuit of operational excellence.

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