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Integrating IoT and Big Data Analytics for Smart Paint Manufacturing Facilities

Raviteja Meda[1*]

[1*]Lead Incentive Compensation Developer, rvtjmeda@gmail.com, ORCID ID: 0009-0009-1578-3865

Abstract
Traditional manufacturing systems are currently undergoing digital transformation by integrating Identification, Sensing, and Communication technology. Mass Unstructured data from structured and unstructured data sources are generated by smart manufacturing equipment and applications in Internet of Things (IoT) powered smart factories. The rapidly changing manufacturing environment produces a variety of challenges in ensuring production and operation efficiency and delivering business values. There's an urgent need for businesses to harness, analyze and gain intelligence from these derived data. Big Data Analytics (BDA), a pioneer in the manufacturing field, focuses on dealing with these 4 V's of Big Data (Volume, Variety, Velocity, and Veracity) through advanced data processing, integration, analysis, machine learning, predictive and prescriptive modelling that assist with data-driven decision-making and optimization in the manufacturing process. While several BDA techniques such as preprocess data, build descriptive models, perform huge-scale data mining and run machine learning predictive models are developing in the manufacturing field, nowadays many manufacturers lag behind in adopting BDA into their operations. This paper, through a systematic literature review, aims to analyze the styles of the existing research and see if they can provide panoramic views toward the integration of BDA and smart manufacturing systems. Seven foundational perspectives based on which the reviewed papers are classified include definitions, applications, architecture, models, methods or techniques, implementations, and reviews or surveys.

Keywords: Smart paint manufacturing facilities, Internet of Things, big data, monitoring, data analytics, prognosis, engineering knowledge transfer, Industry 4.0 technology, Smart Manufacturing, IoT in Paint Industry, Big Data Analytics, Predictive Maintenance, Real-time Monitoring, Industry 4.0,Sensor-based Quality Control, Industrial IoT (IIoT),Smart Factory Solutions, Process Optimization, Data-driven Manufacturing, Automated Paint Production, Manufacturing Analytics, Digital Twin Technology, Energy Efficiency in Paint Plants.

1. Introduction

Industrial analytics is a scientific area focusing on computational approaches for understanding and analyzing industrial systems and processes. Nowadays, several phenomena in manufacturing are difficult to understand and originally driven by events collected through technologies such as the Internet of Things, IoT Clouds, and big data analytics. However, in complex manufacturing processes, corresponding technologies are typically scarce, making the problem even more difficult. Therefore, the relation between complex manufacturing processes and the requirements for continuously improving them in an uncertain environment remains an open issue. To address this gap, an integrated smart manufacturing facilities approach based on the IoT paradigm and cloud-based big data analytics capable of enabling a better understanding of complex systems are proposed and the requirements arising from such systems are analyzed. Methods addressing each requirement are developed, and significant results are illustrated in a case study of a paint manufacturing facility.
Considerable changes brought on by the Internet of Things, Cloud computing, and big data analytics have been reshaping the manufacturing sector toward smart facilities that are capable of continuously sensing, understanding, and decision-making changes in complex manufacturing processes.

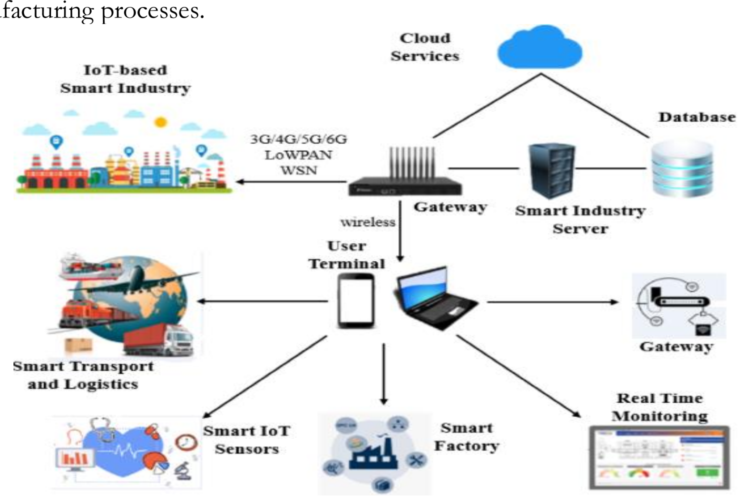

Fig 1: IoT in Manufacturing

1.1. Background and significance

In the past five years, the Internet of Things (IoT) and Big Data have been rapidly developing in manufacturing. Nevertheless, smart manufacturing and intelligent decision-making systems can be substantially realized only with the integration of IoT and Big Data across the manufacturing facilities. In smart paint manufacturing processes, the auto paint thickness varied from normal 120 um to over 1000 um in a few minutes in only one workstation, which leads to defective painted cabinets. In the manufacturing of high precision stepping motors, pulling coil assembly with too high force assembly by 200 N instead of normal 20 N leads to major defects. Even after manufacturing, there are still different kinds of defects, such as dry coating and pinholes, which cannot be detected by normal smart cameras. Incorporating artificial intelligence and pattern recognition in combination with IoT and big data may allow earlier detection of these problems and enhance efficiency.
Smart Manufacturing Facilities Smart solder paste printing has a direct impact on retaining the right solder paste volume on PCB due to open solder joints, reducing false starts, which happen when solder paste is overprinted, leading to excessive solder on the joints and excessive cleaning downtime. For typical PCB4600 series, solder paste volume is verified with volume measurement using high-resolution imaging lasers.

Equ 1: Sensor Data Acquisition Model

$$S_i(t) = f(P(t), T(t), H(t), M(t)) + \epsilon_i(t)$$

Where:

- $P(t)$ = pressure
- $T(t)$ = temperature
- $H(t)$ = humidity
- $M(t)$ = material flow rate
- $\epsilon_i(t)$ = measurement noise/error

2. Overview of Smart Manufacturing

Smart manufacturing integration of IoT and AI technologies to form an intelligent self-operation production system that possesses the ability of automatic assembly line arrangement, fault diagnosis, and quality prediction. It is not only conducive to the improvement of production efficiency and high quality but also helps to regulate production planning and policy making. To date, manufacturing data source is facing an explosive growth since the advent of the IoT technology. The traditional enterprise resource planning (ERP) system and manufacturing execution system (MES) have been extended and upgraded timely. There is a brain-to-brain communication and control between humans and machines as to complete production activities. In face of such heterogeneous and massive manufacturing data stream generated by industrial IoT devices, automatic and intelligent data-driven smart paint manufacturing decision cycles are then anticipated to achieve also some challenging research issues such as one batch production process completion prediction, multiple batches production process arrangement and scheduling take place in dynamic environment, and key parameters influencing on production quality prediction. However, converting data into actionable insight is still one of the most challenges faced by industries nowadays. The data as well as data analytics technology play a pivotal role in the implementation of smart manufacturing. A cyber-physical system (CPS)-based smart paint manufacturing model is proposed to enhance both production efficiency and quality of painted parts through better integration and utilization of IoT enabled data and AI based data models. Meanwhile, the challenges and future works regarding smart paint manufacturing systems are also pointed out. Due to the complex and dynamic characteristics of paint manufacturing, paint production exhibits highly multivariable, nonlinear, time-varying, and coupling systems.

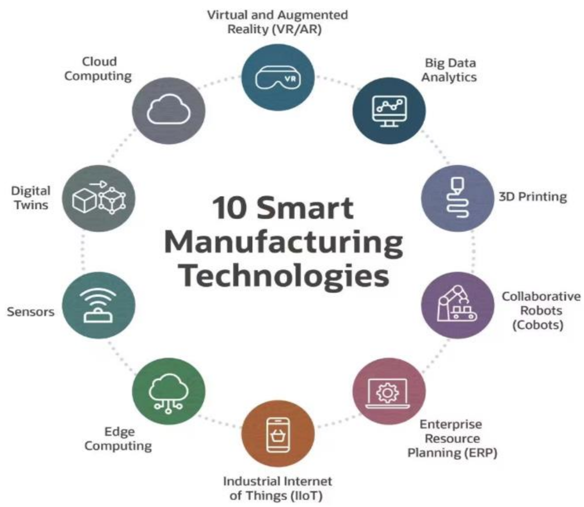

Fig 2: Smart Manufacturing

2.1. Research design

The research adopts a case study approach, with a focus on the smart manufacturing of paint at AkzoNobel in Sweden. Stakeholders relevant to the research topic and scope were identified with the support of field experts from AkzoNobel. Consequently, four interviews were held at AkzoNobel's site in Stenungsund. The interviewees had a manufacturing-related technical background and were part of AkzoNobel's strategy group for digital manufacturing. The interviews took place in a semi-structured format facilitated by open questions followed by probing ones. Two types of questions were constructed: situational questions to gather background information of the interviewees' companies, as well as opinion and comeback questions to collect elaborated perceptions of what challenges and drivers the companies faced.

Each interview lasted about 60–80 minutes. Expensive data collectors and sensors are already in place at AkzoNobel's paint manufacturing facilities. However, excessive data streams arise from them. Consequently, the key challenges include integrating and storing sensor data, exploring them with machine learning, and providing their insights into the supply chain with the software. After finishing the four interviews, a cross-case analysis was conducted to synthesize relative in-depth insights of the four interviewees addressing the same questions. To enhance the validity and reliability of the cross-case analysis, the interview reports were sent back to the interviewees for verification.

Next, the results and discussion are presented, which are accompanied by topical framing to give the reader a clear understanding of the flow of the analysis. The results section is divided into four subsections in correspondence with the key factors impacting the researcher's understanding of the research topic. In the discussion section, three topics are put forward to connect the individual subsections with the overall paper objective.

3. The Role of IoT in Manufacturing

The advent of data-based resource networks and Internet of Things (IoT) technology has enabled the digitization of a new generation of CNC manufacturing equipment and assembly-line automation technology, generating a vast amount of data about the intelligent manufacturing industry, which has all the attributes of Big Data: volume, velocity, variety, and veracity. Big Data analysis is the same as that of manufacturing data with the data dimensions of multi-source, multi-level, and multi-modal, and more importantly, the manufacturing industry is a high-frequency data generation environment which poses great daily challenges to data storage, transmission, analysis, and visualization. In order to process the original massive data, it is crucial to pick out the more relevant data before analysis in the Big Data analysis process. In a smart paint supply chain, the cutting, polishing, and coating quality analysis of automotive body kinetics construction parts is mainly realized through various types of perception data acquisition based on cameras/scanners (2D/3D), and ultraviolet/visible/infrared spectral analysis sensors for surface quality inspection, which generates a large amount of data. However, a small percentage of defect data is interspersed with a large amount of redundant signal data. A one-sigma decision framework was created to pick out the more relevant montages before quality analysis since suspicious defects are totally different from high-quality surfaces and 60-dimensional sub-states are adopted to model the normal conditions of these various kinds of manufacturing processes. Then, the estimation of parameters and noise covariance matrices of the state-space model was first analyzed with the non-parametric particle filter to preprocess the multiple types of perception measurement data for quality analysis study with a comprehensive motion-visual-thermal setup. Once the suspicious defects were identified accurately, a data scheduling strategy was proposed in light of the operating characteristics of data bandwidth and latency of various Big Data analysis methods in order to achieve more efficient defections with faster feedback latency and high accuracy. The use of IoT technology in manufacturing meets the need for automation, clearer process control, and analysis of work and machine faults. Internet-of-Things-based manufacturing proposes the idea of transforming traditional manufacturing into smart manufacturing, which emphasizes flexibility, adaptation, and rapid reaction to customer demands. Intelligent Object Architecture (IoA) provides a solution to architecture problems in traditional IoT deployment. Big data plays an important role in cloud-based manufacturing, establishes a bridge between IoT and cloud technology, and discusses the applications of cloud-based IoT technology in manufacturing. A cloud service platform based on industrial utility is designed and implemented. The architecture of the cloud service platform is presented as a new functional module added to existing clouds in order to transform traditional clouds to manufacturing clouds.

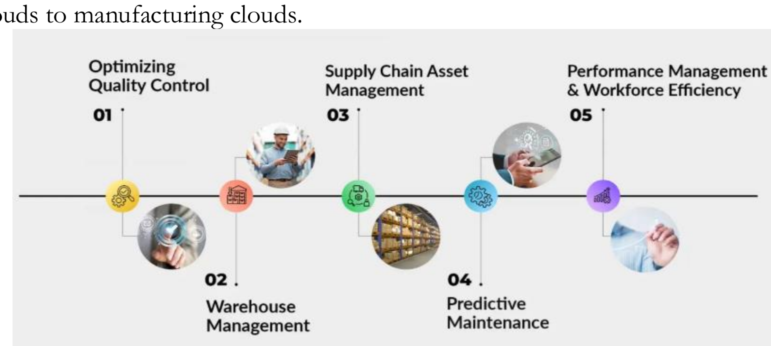

Fig 3: IoT in Manufacturing

3.1. Definition and Key Concepts

With the rapid development of smart manufacturing technology, the manufacturing industry has entered the era of Big Data. Manufacturing is big data-driven, and much attention is being paid to its application by various stakeholders. Big Data generated in the manufacturing process can be broadly categorized as structured, semi-structured, and unstructured data according to data types. Structured data refers to the well-structured data that can be stored in a relational database. Semi-structured data refers to the "soft" data having some level of organization and tag to separate semantic elements. Unstructured data includes various data types that cannot be stored in the format of a traditional database, making it more difficult to identify, analyze, and visualize. Big Data is also characterized by its high volume, rapid growth, and complexity. The four Vs (Volume, Variety, Velocity, and Veracity) should be considered in Big Data applications. Also, big data refers to a basic computing paradigm to capture, store, manage, analyze, and visualize the data as well as methods to handle these tremendous amounts of data. The above definitions focus on big data dimensions and processing technologies in the big data context.

Equ 2: Big Data Predictive Maintenance Model

$$P_f(t) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n)}}$$

Where:

- $P_f(t)$ = probability of equipment failure at time t
- x_i = features from sensor data (e.g., vibration, temperature)
- β_i = learned parameters from historical data

3.2. Benefits of IoT Integration

The integration of IoT sensors and devices into the field of paint manufacturing can create a smarter manufacturing site to accommodate the new needs raised from the Industry 4.0 initiative. The IoT devices are embedded into the factories and used to gather data from the manufacturing environment. Meanwhile, in order to obtain insight from the gathered data and find action to be taken to improve the operation, data analytics techniques can be applied to the data collected [3]. The aggregated time series data sets can provide overall views of the production conditions, and machine learning techniques can be adopted to realize predictive analyses such as forecast and anomaly detection.

The installation of IoT devices in the paint manufacturing field can ensure the operability and availability of the manufacturing facilities by continuously monitoring the working status of the facilities and sending alerts when abnormal conditions take place. Moreover, a batch-level view of the paint manufacturing is provided by accumulating the data from the factory and visualizing the information in a time-series manner. In the case of an alert triggered, the signals can be reconstructed into a sequence, and an automatic differential sequence generator is designed to create the autonomous action to be taken according to that as needed for the facilities. A simulation is deployed to interact with the event using blockade and decrements since learning from the operating conditions is a crucial part of the system.

This integrated mechanism can therefore enhance the operation capability of the paint manufacturing area by improving the stability of facilities as well as securing the availability of overdue productions. The underlying needs of the industry 4.0 initiative can be satisfied by building an intelligent manufacturing ecosystem. The acquisition of the opinions from domain experts can help to ensure the accuracy of the model and results. Furthermore, the designs of the IoT devices and the data aggregation mechanism should take into account the data security and privacy.

4. Big Data Analytics in Manufacturing

Modern manufacturing involves a growing number of distributed intelligent systems, such as sensors, actuators, Industrial IoT devices, and manufacturing equipment, that produce data throughout the manufacturing processes. However, solely collecting massive amounts of data from manufacturing devices is inadequate. To enable the applications of MIoT, manufacturing data should undergo a series of deterministic and/or probabilistic transformation processes, which is known as data analytics. Using AI and other data processing methods for data analytics, smart manufacturing is devised as a new paradigm towards enhancing the efficiency and quality of manufacturing, and new knowledge could be discovered from captured manufacturing data.

With the growing complexity of manufacturing processes, intelligent manufacturing systems, the integration of Internet of Things (IoT), and big data analytics based on these devices are becoming a trend. Data analytics in the manufacturing context has received increased attention for the continuous analysis of the data generated, stored, and transmitted by connected smart manufacturing resources, machines, and applications. The breadth of analysis varies from traditional business intelligence up to complex deep learning algorithm based analysis with the development of cloud computing, big data technology, and AI, machine learning, deep learning technology.

Manufacturing Internet of Things (MIoT), as a technology deriving from IoT, was proposed to provide new services for the discrete manufacturing and process manufacturing. Owing to the rapid growth of intelligent sensing, communication, and computing technologies, increasing interest has been put into big data analytics for improving efficiency, productivity, and quality of manufacturing processes and systems based on MIoT. In addition, in-depth discussions, analyses, as well as evaluations on big data analytics for MIoT seem rare, especially when compared with those in other areas such as SDN and VANET.

Fig 4: Big Data Analytics for Smart Manufacturing

4.1. Understanding Big Data

The global manufacturing environment has been changing from earlier standard manufacture with rigid CNC systems to smart manufacturing with flexibility and intelligence. Meanwhile, to achieve more intelligent manufacturing, putting more technologies like Industrial Internet of Things (IIOT), Artificial Intelligence (AI) and Big Data Analytics (BDA) into a manufacturing system has become a trend. Among these technologies, IIOT collects diverse types of data across the system, and BDA studies how to utilize it and present business values. Nowadays, BDA has been a hot research area. Due to the scope and pervasiveness of the manufacturing industry and its associated data, BDA in the manufacturing industry, particularly in the smart paint manufacturing service system, brings in the need of immediate addressing. Only when thorough knowledge around manufacturing data and analytic techniques is presented and suggested, the smart paint manufacturing service system could be further developed.

Big data is an umbrella concept, including 1) volume: the quantity of data has exploded it is widely recognized that the world is encircled by data; 2) velocity: both the ingrate and the processing of data should be rapid and on-time; 3) variety: the data can take different structure and format; and 4) veracity: the data collected may suffer from inaccuracy and uncertainness. Some researchers noted that existing data could also be categorized into structured data, semi-structured data and unstructured data according to their content. Structured data like relational data in capsule format has been studied for decades and a lot of analytic techniques are available. Semi-structured data like XML data contains tags to encode the logical structure of the data, hence facilitating the understanding of its content for computer systems, while preserving the flexibility. Descriptive data like image, audio and video are unstructured, and there is little applicable knowledge and algorithms to analyze this messy data.

4.2. Data Processing Techniques

In the implementation of the Smart Paint Manufacturing Facilities Pilot Plant, SCiO has developed a large-scale Industrial Cyber-Physical System (ICPS) for real-time data collection and monitoring. This ICPS ingests a high volume of measurements monitored by various equipment types, such as programmable logic controllers (PLC) and industrial PCs (IPC). The challenge lies in processing and archiving the increasing volume of data, both for immediate operational needs and long-term analytic purposes. Another obstacle to be solved is the degree of effort required for the platform to scale, depending on the growth of the monitored industrial system. Big Data technologies and cloud computing infrastructures have been applied for analytics on data sent to a cloud-based architecture. However, until this work, platforms like these with on-premises edge infrastructures were not adequately supported.

IoT (Internet of Things) encompasses the overarching infrastructure through which smart connected objects can communicate and interact to provide improved and ubiquitous services. As a key enabler of the IoT, the importance and utility of Big Data analytics have rapidly increased over the last decade. The unprecedented growth of IoT generates large amounts of data, the so-called Big Data. It includes data explosion, heterogeneous data sources, data streaming, data uncertainty, data security and privacy, data quality, data volume, data variety, data velocity, data value, etc. Effective data processing techniques including Data Collection, Data Filtering, Data Compression, Data Analytics are key features to realize Smart Paint Manufacturing Facilities. The data filtering technique is used to filter unnecessary and irrelevant data from the data-outranging manufacturing area. The data compression technique results in significantly smaller storage size. Instead of storing all sensor records at one time, sensor data compression is employed to reduce the size of the data to store on the cloud without losing any important information.

The methodologies of IoT data processing techniques, particularly on Big Data technologies, including Data Collection, Filtering, Compression, and Analytics, are reviewed and discussed. The IoT data processing techniques could provide a reference for researchers and engineers in the area of Smart Manufacturing Facilities. The progress toward better understanding of IoT data processing techniques is presented to explore future research work of big data analytics. In this work, the existing issues of IoT data acquisition, storage, management, filtering, compression, and analytics of big data technologies are summarized and analyzed over their sources of acquisition and interaction.

5. Integration of IoT and Big Data

The rapid growth of IoT-connected sensors and devices in manufacturing has significantly enhanced data collection capabilities, leading to advancements in big data analytics technology over the past decade. Manufacturing companies can leverage this large-scale data collection, storage, and processing capability to drive intelligent manufacturing, optimizing manufacturing processes and operations. In this scenario, industrial IoT plays an essential role in monitoring and controlling key manufacturing operations generating rich and large-scale sensor data. However, the industrial IoT has transformed the

industrial environment into a complicated data environment with various industrial IoT devices from different vendors producing heterogeneous data streams. To unleash the values of industrial IoT, various key technology challenges must be addressed, including heterogeneous data visualization, storage, and analytics.
Data engineering comprises a set of principles, modeling techniques, and methods used to produce, store, and supply data. The field of data engineering began in the 1980s in response to limitations with existing file systems as businesses and organizations began to invest heavily in information technology and computerized data processing. SaaS systems are an emerging category of cloud services frequently employed to fulfill businesses' industry-specific data engineering and analytical activities. Many business intelligence, location intelligence, data integration, and data warehouse services fall within this category. They are typically designed to work in conjunction with databases, data processing engines, and hosted services. Vitis is a software toolchain that enables programming, emulating, debugging, and profiling latency-critical applications across the software-programmable and hardware-accelerated environments. It comprises a comprehensive set of tools, libraries, utilities, and pre-built IP that allow developers to build systems that leverage every element of the data center spectrum, from edge devices to sophisticated accelerator cards, by integrating software with hardware programming and emulation.
The scalable and flexible architecture of cloud-based distributed applications has become a fundamental trend for both consumer and enterprise applications. Cloud computing provides software and services on demand and shared resources for executing highly distributed and parallelized applications according to proven Internet standards, protocols, and interfaces. To realize flexible combinations of any third-party applications deployed on the cloud, a new method is required to describe and develop data transfer protocols between different applications. As big data emerges, cloud computing has also gained much attention for data and storage management. With these new paradigms, the industrial environment has become more complicated, generating oceanic data from various applications. Current successful architectures and solutions targeting specific settings are not appropriate for such an evolving and challenging environment where data is large-scale, heterogeneous, dynamic, and extremely complex.

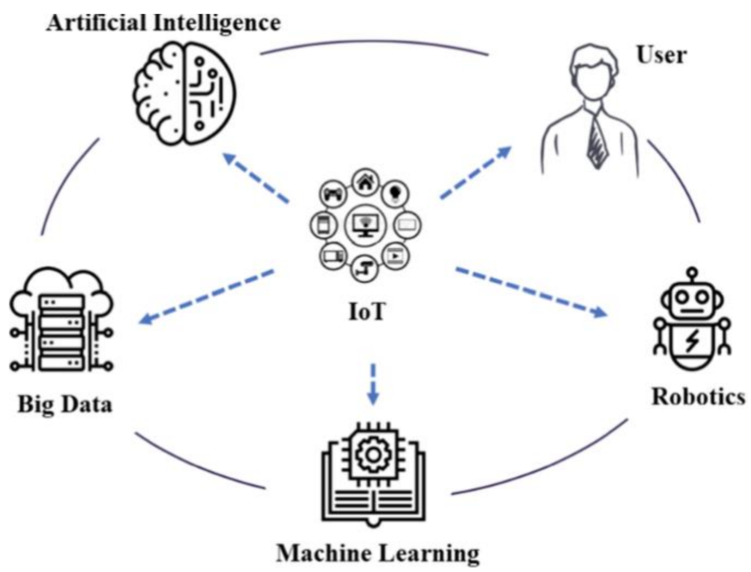

Fig 5: Integration of IoT with big data analytics

5.1. Challenges and Solutions

To date, smart manufacturing still lacks a widely accepted literature framework. In order to address this long-standing issue, this section highlights the potential challenges and solutions in adopting IoT and Big Data technologies in smart manufacturing in three different perspectives, including organizational, management, and technical challenges.
The literature review shows that not all companies are prepared to adopt Smart Manufacturing, a relatively low-impact, high-rate impact solution. This means that significant readiness concerns must be addressed at either the organizational, managerial, or technical level in order for these technologies to be effectively integrated into operational manufacturing processes. Reasons for not adopting the next generation Smart Manufacturing process depend primarily on organizational or management readiness. Very rarely do companies perceive sufficient challenges in the technical field. Nevertheless, ensuring awareness of these readiness challenges is only a first step toward an implementation plan; for each of the three aforementioned categories of readiness, the companies should follow specific ways-of-working approaches in order to handle their own state readiness shortcomings. For instance, processes can be defined and documented, and the documentation reviewed and improved as needed. Additionally, effective training needs to be conducted, and suggestions need to be given to those who are still not completely convinced of the benefits. These suggested approaches can contribute to process transformation by changing the relevant companies' current working practices towards the desired future adoption of Smart Manufacturing technologies.
On the management side, metrics relevant to Smart Manufacturing readiness should be discussed and evaluated, and the changes to these metrics should be communicated to the entire company in a clear and easily interpretable way. Furthermore, broad collaboration both internally, across departments, and externally, across the supply chain, should be initiated. Likewise, dedicated roles for Smart Manufacturing should be appointed, and long-term strategies should be agreed upon. Finally, on the

technical side, a Smart Manufacturing platform should be properly implemented and maintained, and component-level digital twins should be defined.

5.2. Case Studies in Manufacturing

In a fast-evolving digital landscape, companies of all sizes grapple with vast amounts of data priced, but untapped, to drive improvements. The concept of Industry 4.0 has arisen to address the complementary phenomena of hyper-connectivity and digitalization that is seen to constitute a paradigm shift in production systems. Industry 4.0 research has exploded in the past years across multiple disciplines from engineering and computer science to management and organization studies. Advanced manufacturing argues, however, that a real transformation requires far more than simply more data, sensors, and automation. To succeed in the rapidly changing global marketplace, companies need reasons and processes for prioritization and decision-making. Case companies have difficulties in establishing a holistic knowledge trajectory covering everything from the identification of improvement potential to action and feedback loops in practice.

This need for research-based decision support has become evident in a predictive maintenance Industry 4.0 transformation project in a Swedish manufacturing company. The project's focus is on how to ensure that the right data is acquired to answer the right questions, based on the rapid changes in production systems. A number of knowledge challenges associated with each of the data value chain stages are identified and categorized based on the expertise domain from which the knowledge is lacking. A knowledge trajectory that is conducive to integration, is one possible enabler for moving forward from a primarily data-driven analytics to actionable artificial intelligence, enabling a new, more anticipatory and agile, way of working in fast-evolving production environments. A knowledge trajectory that is possible to develop across organizations in a generic manner is important, as digitization efforts often involve a multitude of actors with different cultures, experiences, and levels of motivation.

As a means for knowledge integration across the different knowledge domains, a knowledge trajectory is proposed, enabling integration of analytics, organization, and technical knowledge. The trajectory is generic in nature, allowing for use across organizations, enabling reduction of the knowledge gaps and increased readiness for digitization efforts. The knowledge trajectory is discussed on a high level, leaving further explorations and detailed applications to future studies. A crystallization of the initial analysis, targeting a different level of knowledge integration across the knowledge domains of analytics, organization, and technology was put forth. The trajectory was developed, covering what is often referred to as the challenges of the data value chain.

Equ 3: Energy Consumption Model

$$E(t) = \sum_{i=1}^{n} U_i(t) \cdot P_i(t)$$

Where:

- $U_i(t)$ = utilization rate of machine i
- $P_i(t)$ = power consumption of machine i at time t

6. Smart Paint Manufacturing Facilities

This paper proposes a generalized architecture to integrate existing and new monitoring devices and dashboards in a smart paint manufacturing facility utilizing IoT sensors and data analytics techniques. Such facilities consist of a large number of devices that generate a huge amount of data. The computational resources available on-premises with current Industry 4.0 technologies become of limited capacity and efficiency to deal with the quantity of data generated and their real-time requirements.

With the advancements of the Industry 4.0 paradigm along with the rapid development of recent technologies in edge computing and Big Data analytics, new opportunities are foreseen for manufacturers to improve Quality, Reliability, Performance, and to minimize Cost. This paper discusses the integration of IoT sensors and Big Data analytics techniques in a smart paint manufacturing facility to allow real-time monitoring of asset states and process KPIs. Strategies to properly design and implement an Edge-Cloud architecture to connect a wide variety of existing and new devices leveraging data visualization dashboards are proposed. Using a correct segmentation of the analytics tasks between the Edge and the Cloud, computational costs can be significantly reduced and the real-time requirement of the monitoring applications satisfied at each operational/deployment level of the architecture. Based on the analytics capabilities of such an approach, manufacturers can respond in time to deviations in chemical mixtures/process variability/outages and reduce both the occurrence and the impact of quality anomalies on the production line resulting in improved performance and reduced cost.

Prior to a smart approach, traditional manufacturing was typically focused on the use of automated equipment with a limited degree of connectivity. Data, when collected, was stored in individual databases providing lagging indicators of process performance that took considerable time and effort to retrieve and process before meaningful insight could be obtained. The various stages undertaken to facilitate the integration of IoT and Big Data in the facility are described, noting the corresponding implications for resource usage.

Fig : IoT integrators

6.1. Current Trends in Paint Manufacturing

In this paper, the context of smart factories in the manufacturing sector is outlined, focusing on the development of smart paint manufacturing facilities. There is a clear need for more predictive analytics and preventive decision-making to reduce the risk of unplanned equipment failure, interrupted production or product quality issues. This paper combines current smart manufacturing technology trends and cyber-physical systems theory with multiple case studies on paint manufacturing experts. Case studies were executed through interviews, site visits and workshops together defining 46 use cases of predictive analytics in paint manufacturing. Those use cases were categorized into a 3-stage framework with the aim to increase the decision-making level of manufacturing information and related systems. A set of generic enabling technologies to realize the framework. It was shown that there is a potential to increase the amount of predictive analytics in paint manufacturing, but also present barriers to doing so. In particular, multiple case studies on paint manufacturing facilities in the Nordic countries are presented. These case studies comprised interviews, workshops and site visits from which current predictive analytics use cases and feedback on use case implementation were collected. From these studies, a framework categorizing use cases into three stages based on predictive capability was created, detailing use cases enabling Smart Paint Manufacturing Facilities. Worldwide paint production is growing steadily at just over 5% per year and in an intelligent manufacturing context, new paints or varnishes that dry quickly are likely to be requested. Paint manufacturing facilities have a large variety of processes including multiple stages for producing paint delivered to several batch processing process units. The variables in these painting processes are often controlled using data-driven methods, some of these are capable of predictive decision-making. There is still a clear need for more predictive analytics and preventive decision-making to reduce the risk of unplanned equipment failure and for disruptive event prediction to ultimately reduce the risk of interrupted production or product quality issues.

6.2. IoT Applications in Paint Production

IoT Applications are growing more and more relevant in paint production, such as the IoT platform for monitoring analog gauges. This digital transformation brings more automation, more accurate parameters collection, prevents errors, and needs less staff to handle the same monitoring needs. Also, Industry 4.0 technologies allow a changing paradigm for production systems, generating data streams that are useful in the right context. This can increase quality control by monitoring parameters that were not previously collected, introducing automation in inspection systems. Along with camera systems, there's the IoT platform that will make detected problems automatically notify the users. Poor Supply Chain Management often leads to prioritizing output over efficiency, decreasing profit and lowering customer satisfaction. More information in the decision-making systems of the factories can change this. Increased traceability and uptime for predictive maintenance can optimize the scheduling of machinery maintenance. Better planning and scheduling for inventory use and work orders can incorporate delays from raw material orders. In these scenarios, the OEE, a composite key performance indicator that aggregates three others (availability, performance, and quality) can help understand efficiency problems better, and become more precise to take corrective actions.

Most of the paint production experiences are made in discrete batch mode. Several consequences arise from this process type, prioritizing productivity over efficiency. The raw materials for paint production are usually more vulnerable to degradation or contamination, which often results in stock-outs and needs the implementation of JIT and ATO practices. Sometimes, to ensure changing mix proportions satisfied the batch time constraints, stalled batch processes are reactivated after long times in hot stand-by, oftentimes in unpredicted states. All of these process states and material flows need careful understanding and monitoring, and turn batch processes more complex to control and improve. Type of paint products created accuracy expectations (in dry time, color stability, color accuracy, hiding power, etc.), productions need also on-line quality control. New Industry 4.0 technologies, such as IoT technologies, big data analytics, and advanced simulations can bring solutions here. Understanding the current process status in real-time allows paint production facilities to manage stock-outs, consecutive mismatches, etc. A data collection and management architecture can be modelled contrary, the quality control framework to design an appropriate set of quality controls and diagnosis methods.

7. Conclusion

The presented concept utilizes best-practice Smart Manufacturing paradigms to digitally transform an entire paint manufacturing facility. Such facilities are complex and contain various production lines, materials, machines, and processes. Gaining full situational awareness requires integrating data across levels - from the managers' administrative-level MES to the operators' machine-level PLCs. These systems were frequently hard-coded to integrate, limiting flexibility. This, in combination with a large heterogeneous data space, resulted in not sufficiently explored IoT and Big Data Analytics integration opportunities.

The proposed BDA tool realizes knowledge-intensive data readiness by crowd-sourcing and integrating data according to a pre-defined taxonomy. The resulting data trails are then analyzed using a library of generic and custom, user-friendly ML/AI functions. Naturally, the operations team, fast-paced in allegiance to the production schedule, can implement only a few analyses. Hence, instead of delivering merely a long list of computations to choose from, it should recommend analyses with a pre-defined priority, input parameters, and ready implementation. Since data and analyses are integrated and the latter returns prediction results for further conditional executions, an interruption-free execution path and full machinable enhancement are achievable.

Relevant knowledge gathered during the Smart Paint Manufacturing Facilities research and development project may be excellent progress in this direction. The proposed implementation roadmap can assist in further pursuing the vision of the Smart Paint Manufacturing Facilities concept. Ultimately, the manuscript may serve as a valuable case study for implementing data-driven Digital Twin solutions in similar industries.

7.1. Future Trends

On April 6, 2019, the worlds of big data and the Internet of Things (IoT) were disrupted when the chief engineer of a UK paint manufacturing facility utilizing a data capture and analysis platform suddenly departed. Their data scientist, left without guidance and understanding of the platform, spent six months producing tedious and low fidelity analyses. In October 2019, it was written into a pandemic crisis novel about how someone with a strong background in big data interrogation might step into the breach. Seven days before the early 2020 lockdown was announced, that individual joined the company. In-house tools had only been partially utilized and needed to be developed further. An academic with strong background knowledge of data capture and data presentation was brought into the fold. That partnership grew with the benefit of strong technical assistance on both sides. Amid a continuous deluge of growing amounts of data, the cyclical nature of the ALPS system created its own challenges.

Throughout 2021, focus shifted inward, embracing the strategic pillars of the organization and the concepts of lean manufacturing. Monthly rigorously arranged board meetings saw the coaching of individuals to consider success in terms of positive deviation from normal as opposed to "fire-fighting." Targets were set, strategies planned, and educational opportunities seized. Fast forward to 2023—new premises, state-of-the-art IOT die dendrite silo installation, new data recording understanding, big data analytics redundancy, and several data and programming science staff vacancies. The opportunity is now on the horizon to shift from a near-surface pre-occupancy with the data, exploration visualization, and high-level dashboards to the construction of more sophisticated, deeper-rooted controllable analytics for performance improvement and creative control.

Gaps at this phase can include reliance on too few individuals with limited breadth of big data and programming science knowledge, direct reliance upon commercial software vendors for data analysis consultation instead of capitalizing on continuous education opportunities at a minimum staff level, not recruiting appropriate staff from the outset to construct analytics to meet strategic and operational needs, and not exclusively arming data capture and extraction operators with the abilities to analyze the already captured data.

8. References

[1] Vankayalapati, R. K. (2020). AI-Driven Decision Support Systems: The Role Of High-Speed Storage And Cloud Integration In Business Insights. Available at SSRN 5103815.

[2] Sondinti, L. R. K., & Yasmeen, Z. (2022). Analyzing Behavioral Trends in Credit Card Fraud Patterns: Leveraging Federated Learning and Privacy-Preserving Artificial Intelligence Frameworks.

[3] Kannan, S. (2022). The Role Of AI And Machine Learning In Financial Services: A Neural Networkbased Framework For Predictive Analytics And Customercentric Innovations. Migration Letters, 19(6), 985-1000.

[4] Harish Kumar Sriram. (2022). AI-Driven Optimization of Intelligent Supply Chains and Payment Systems: Enhancing Security, Tax Compliance, and Audit Efficiency in Financial Operations. Mathematical Statistician and Engineering Applications, 71(4), 16729–16748. Retrieved from https://philstat.org/index.php/MSEA/article/view/2966

[5] Chava, K. (2022). Redefining Pharmaceutical Distribution With AI-Infused Neural Networks: Generative AI Applications In Predictive Compliance And Operational Efficiency. Migration Letters, 19(S8), 1905-1917.

[6] Komaragiri, V. B. (2022). AI-Driven Maintenance Algorithms For Intelligent Network Systems: Leveraging Neural Networks To Predict And Optimize Performance In Dynamic Environments. Migration Letters, 19, 1949-1964.

[7] Chakilam, C. (2022). Generative AI-Driven Frameworks for Streamlining Patient Education and Treatment Logistics in Complex Healthcare Ecosystems. Kurdish Studies. Green Publication. Kurdish Studies. Green Publication. https://doi. org/10.53555/ks. v10i2, 3719.

[8] Nuka, S. T. (2022). The Role of AI Driven Clinical Research in Medical Device Development: A Data Driven Approach to Regulatory Compliance and Quality Assurance. Global Journal of Medical Case Reports, 2(1), 1275.

[9] Burugulla, J. K. R. (2022). The Role of Cloud Computing in Revolutionizing Business Banking Services: A Case Study on American Express's Digital Financial Ecosystem. Kurdish Studies. Green Publication. https://doi. org/10.53555/ks. v10i2, 3720.

[10] Pamisetty, A. (2022). Enhancing Cloud native Applications WITH Ai AND Ml: A Multicloud Strategy FOR Secure AND Scalable Business Operations. Migration Letters, 19(6), 1268-1284.

[11] Anil Lokesh Gadi. (2022). Transforming Automotive Sales And Marketing: The Impact Of Data Engineering And Machine Learning On Consumer Behavior. Migration Letters, 19(S8), 2009–2024. Retrieved from https://migrationletters.com/index.php/ml/article/view/11852

[12] Someshwar Mashetty. (2022). Enhancing Financial Data Security And Business Resiliency In Housing Finance: Implementing AI-Powered Data Analytics, Deep Learning, And Cloud-Based Neural Networks For Cybersecurity And Risk Management. Migration Letters, 19(6), 1302–1818. Retrieved from https://migrationletters.com/index.php/ml/article/view/11741

[13] Pandiri, L., & Chitta, S. (2022). Leveraging AI and Big Data for Real-Time Risk Profiling and Claims Processing: A Case Study on Usage-Based Auto Insurance. In Kurdish Studies. Green Publication. https://doi.org/10.53555/ks.v10i2.3760

[14] Recharla, M., & Chitta, S. (2022). Cloud-Based Data Integration and Machine Learning Applications in Biopharmaceutical Supply Chain Optimization.

[15] Nandan, B. P., & Chitta, S. (2022). Advanced Optical Proximity Correction (OPC) Techniques in Computational Lithography: Addressing the Challenges of Pattern Fidelity and Edge Placement Error. Global Journal of Medical Case Reports, 2(1), 58–75. Retrieved from https://www.scipublications.com/journal/index.php/gjmcr/article/view/1292

[16] Srinivasarao Paleti. (2022). Adaptive AI In Banking Compliance: Leveraging Agentic AI For Real-Time KYC Verification, Anti-Money Laundering (AML) Detection, And Regulatory Intelligence. Migration Letters, 19(6), 1253–1267.

[17] Pallav Kumar Kaulwar. (2022). Data-Engineered Intelligence: An AI-Driven Framework for Scalable and Compliant Tax Consulting Ecosystems. Kurdish Studies, 10(2), 774–788. https://doi.org/10.53555/ks.v10i2.3796

[18] Koppolu, H. K. R. (2022). Advancing Customer Experience Personalization with AI-Driven Data Engineering: Leveraging Deep Learning for Real-Time Customer Interaction. Kurdish Studies. Green Publication. https://doi.org/10.53555/ks. v10i2, 3736.

[19] Dodda, A. (2022). Strategic Financial Intelligence: Using Machine Learning to Inform Partnership Driven Growth in Global Payment Networks. International Journal of Scientific Research and Modern Technology, 1(12), 10–25. https://doi.org/10.38124/ijsrmt.v1i12.436

[20] Jeevani Singireddy,. (2022). Leveraging Artificial Intelligence and Machine Learning for Enhancing Automated Financial Advisory Systems: A Study on AIDriven Personalized Financial Planning and Credit Monitoring. Mathematical Statistician and Engineering Applications, 71(4), 16711–16728. Retrieved from https://philstat.org/index.php/MSEA/article/view/2964

[21] Challa, S. R. (2022). Optimizing Retirement Planning Strategies: A Comparative Analysis of Traditional, Roth, and Rollover IRAs in LongTerm Wealth Management. Universal Journal of Finance and Economics, 2(1), 1276.

[22] Lakkarasu, P., & Kalisetty, S. Hybrid Cloud and AI Integration for Scalable Data Engineering: Innovations in Enterprise AI Infrastructure[23] Ganti, V. K. A. T., & Valiki, S. (2022). Leveraging Neural Networks for Real-Time Blood Analysis in Critical Care Units. KURDISH. Green Publication. https://doi. org/10.53555/ks. v10i2, 3642.

[24] Kothapalli Sondinti, L. R., & Syed, S. (2022). The Impact of Instant Credit Card Issuance and Personalized Financial Solutions on Enhancing Customer Experience in the Digital Banking Era. Universal Journal of Finance and Economics, 1(1), 1223. Retrieved from https://www.scipublications.com/journal/index.php/ujfe/article/view/1223

[25] Annapareddy, V. N. (2022). Innovative Aidriven Strategies For Seamless Integration Of Electric Vehicle Charging With Residential Solar Systems. Migration Letters, 19(6), 1221-1236.

[26] Sriram, H. K. (2022). AI Neural Networks In Credit Risk Assessment: Redefining Consumer Credit Monitoring And Fraud Protection Through Generative AI Techniques. Migration Letters, 19(6), 1017-1032.

[27] Komaragiri, V. B., & Edward, A. (2022). AI-Driven Vulnerability Management and Automated Threat Mitigation. International Journal of Scientific Research and Management (IJSRM), 10(10), 981-998.

[28] Chakilam, C. (2022). Integrating Generative AI Models And Machine Learning Algorithms For Optimizing Clinical Trial Matching And Accessibility In Precision Medicine. Migration Letters, 19, 1918-1933.

[29] Malempati, M. (2022). Machine Learning and Generative Neural Networks in Adaptive Risk Management: Pioneering Secure Financial Frameworks. Kurdish Studies. Green Publication. https://doi. org/10.53555/ks. v10i2, 3718.

[30] Challa, K. (2022). Generative AI-Powered Solutions for Sustainable Financial Ecosystems: A Neural Network Approach to Driving Social and Environmental Impact. Mathematical Statistician and Engineering.

[31] Anil Lokesh Gadi. (2022). Connected Financial Services in the Automotive Industry: AI-Powered Risk Assessment and Fraud Prevention. Journal of International Crisis and Risk Communication Research , 11–28. Retrieved from https://jicrcr.com/index.php/jicrcr/article/view/2965

[32] Srinivasarao Paleti. (2022). Fusion Bank: Integrating AI-Driven Financial Innovations with Risk-Aware Data Engineering in Modern Banking. Mathematical Statistician and Engineering Applications, 71(4), 16785–16800.

[33] Pallav Kumar Kaulwar. (2022). Securing The Neural Ledger: Deep Learning Approaches For Fraud Detection And Data Integrity In Tax Advisory Systems. Migration Letters, 19(S8), 1987–2008. Retrieved from https://migrationletters.com/index.php/ml/article/view/11851

[34] Dodda, A., Lakkarasu, P., Singireddy, J., Challa, K., & Pamisetty, V. (2022). Optimizing Digital Finance and Regulatory Systems Through Intelligent Automation, Secure Data Architectures, and Advanced Analytical Technologies.

[35] Operationalizing Intelligence: A Unified Approach to MLOps and Scalable AI Workflows in Hybrid Cloud Environments. (2022). International Journal of Engineering and Computer Science, 11(12), 25691-25710. https://doi.org/10.18535/ijecs.v11i12.4743

[36] Vankayalapati, R. K., & Pandugula, C. (2022). AI-Powered Self-Healing Cloud Infrastructures: A Paradigm For Autonomous Fault Recovery. Migration Letters, 19(6), 1173-1187.

[37] Kalisetty, S., Vankayalapati, R. K., Reddy, L., Sondinti, K., & Valiki, S. (2022). AI-Native Cloud Platforms: Redefining Scalability and Flexibility in Artificial Intelligence Workflows. Linguistic and Philosophical Investigations, 21(1), 1-15.

[38] Sriram, H. K. (2022). Integrating generative AI into financial reporting systems for automated insights and decision support. Universal Journal of Finance and Economics, 2(1), 115–131. Retrieved from https://www.scipublications.com/journal/index.php/ujfe/article/view/1299

[39] Malempati, M. (2022). AI Neural Network Architectures For Personalized Payment Systems: Exploring Machine Learning's Role In Real-Time Consumer Insights. Migration Letters, 19(S8), 1934-1948.

[40] Vamsee Pamisetty, Lahari Pandiri, Sneha Singireddy, Venkata Narasareddy Annapareddy, Harish Kumar Sriram. (2022). Leveraging AI, Machine Learning, And Big Data For Enhancing Tax Compliance, Fraud Detection, And Predictive Analytics In Government Financial Management. Migration Letters, 19(S5), 1770–1784. Retrieved from https://migrationletters.com/index.php/ml/article/view/11808

[41] Kishore Challa, Jai Kiran Reddy Burugulla, Lahari Pandiri, Vamsee Pamisetty, Srinivasarao Paleti. (2022). Optimizing Digital Payment Ecosystems: Ai-Enabled Risk Management, Regulatory Compliance, And Innovation In Financial Services. Migration Letters, 19(S5), 1748–1769. Retrieved from https://migrationletters.com/index.php/ml/article/view/11807

[42] Botlagunta Preethish Nadan. (2022). Emerging Technologies in Smart Computing, Sustainable Energy, and Next-Generation Mobility: Enhancing Digital Infrastructure, Secure Networks, and Intelligent Manufacturing. Mathematical Statistician and Engineering Applications, 71(4), 16749–16773. Retrieved from https://philstat.org/index.php/MSEA/article/view/2967

[43] Kaulwar, P. K. (2022). The Role of Digital Transformation in Financial Audit and Assurance: Leveraging AI and Blockchain for Enhanced Transparency and Accuracy. Mathematical Statistician and Engineering Applications, 71 (4), 16679–16695.

[44] Karaka, L. M. (2021). Optimising Product Enhancements Strategic Approaches to Managing Complexity. Available at SSRN 5147875.

[45] Katnapally, N., Murthy, L., & Sakuru, M. (2021). Automating Cyber Threat Response Using Agentic AI and Reinforcement Learning Techniques. J. Electrical Systems, 17(4), 138-148.

[46] Boppana, S. B., Moore, C. S., Bodepudi, V., Jha, K. M., Maka, S. R., & Sadaram, G. (2021). AI And ML Applications In Big Data Analytics: Transforming ERP Security Models For Modern Enterprises.

[47] Chinta, P. C. R., & Karaka, L. M.(2020). AGENTIC AI AND REINFORCEMENT LEARNING: TOWARDS MORE AUTONOMOUS AND ADAPTIVE AI SYSTEMS.

[48] Velaga, V. (2022). Enhancing Supply Chain Efficiency and Performance Through ERP Optimization Strategies.