Educational Administration: Theory and Practice
2024, 30(5), 14235-14245
ISSN: 2148-2403
https://kuey.net/
Research Article

Integrating Iot, AI, And Big Data For Enhanced Operational Efficiency In Smart Factories

Dinesh Kalla[1*], Nathan Smith[2]

[1*]Microsoft Corp, dineshkalla14@outlook.com
[2]NathanSmith289@outlook.com

Citation: Dinesh Kalla et al. (2024), Integrating Iot, AI, And Big Data For Enhanced Operational Efficiency In Smart Factories, *Educational Administration: Theory and Practice*, 30(5), 14235-14245
Doi: 10.53555/kuey.v30i5.6492

ARTICLE INFO

ABSTRACT

Smart factories built on new technologies such as the Internet of Things (IoT), machine learning (ML), and big data are emerging as the next generation of manufacturing techniques. However, existing research fails to answer how these techniques can be effectively integrated to improve the efficiency of the plants. In this paper, a reservation-based eXtended Boolean Network (RXBN) model is proposed. The system consists of six stages, including perception, reservation, decision, operation, interpretation, and adjustment. For each stage, its role, goal, and corresponding technologies are discussed, with a special focus on the use of IoT, ML, and big data. In the stage of perception, IoT technologies are proposed to acquire various kinds of data. Then, reservation and decision stages follow to assess system risks and decide the correct reaction. Different from the traditional use of deep learning to replace the Boolean model, it is proposed to use reinforcement learning to help the latter make informed decisions. Finally, these techniques are confirmed to be of great use in several application scenarios. The results show that RXBN provides a solution that effectively integrates AI, big data, and IoT to improve operational efficiency, for example, reducing maintenance costs, increasing manufacturing supply chain quality, and improving worker safety and health.Control mechanism, data-driven analysis, big data, AI, IoT.

Keywords: Integrating IoT, AI, Industry 4.0, Internet of Things (IoT), Artificial Intelligence (AI), Machine Learning (ML), Smart Manufacturing (SM),Computer Science, Data Science,Vehicle, Vehicle Reliability

1. Introduction

With the advent of Industry 4.0, major advancements in machines and networking for the smart factory are required. Many new technologies constitute Industry 4.0, including the Internet of Things (IoT), big data, artificial intelligence (AI), and cloud computing. The Internet of Things (IoT) connects billions of intelligent devices to the internet. Devices operating within the IoT environment generate diverse data. Cooperating with big data and artificial intelligence (AI), devices can make decisions and recognize business patterns to enhance customer profitability. Big data is the large volume of structured and unstructured data. Big data is significant as it helps to improve operations and make better decisions. Artificial intelligence examines data more deeply than what humans can analyze. The data analytics uses machine learning algorithms to find the various threats for both existing and future attacks. It can help to efficiently prevent, detect, or react to cyber-attacks.The smart factory of Industry 4.0 builds its industrial concepts and methodology with emerging computing infrastructures such as IoT, big data, and AI. This paper introduces some of the concepts that make the Internet of Things "smart factory" possible. Details of facility management and improvement have been discussed. As the main contribution, this paper introduces practically achievable concepts where the practical devices can be built with minimal or no additional cost. The key contents include facility management of air conditioners and computers, poison gas detection using the clustering techniques of particle sensors, and odor classification using AI. The result shows that our built prototype has worked to identify a class of poison gas as predefined using the measured gas value.

Fig 1: AI Enabled IIoT Network Integration.

1.1. Background and Significance

Manufacturing has dominated the industrial sector because it enhances economic growth while offering cheaper and better products for society. As we have entered the stage of the Fourth Industrial Revolution, technological advancements, such as the Internet of Things (IoT) and Artificial Intelligence (AI), have driven a new intelligent platform, the so-called intelligent manufacturing industry system, which is a repositioned smart factory. The objective of the repositioned industry is to satisfy diverse and rapidly changing consumer demand for customized products, which creates challenges related to flexible production capabilities and products and requires tailored combinations of workers, robots, and artificial intelligence to ensure output of exceptional quality. The capabilities of IIoT, AI, and big data have driven unparalleled advancements with the variety and capabilities of factory sensors to carry out the functions of perceptual operation monitoring, remote maintenance, virtual and augmented reality, and production control, which are all part of the process and function of smart manufacturing.

Smart factories are transforming manufacturing from a rigid reprogramming model driven by classical automation systems to a more self-adaptive and self-optimization manufacturing system that is defined by the growing capacity to deal with complex self-regulation, self-awareness, proactiveness, and reliable constraint handling. Improved productivity and value creation for customers and partners through autonomous decision-making, maximum transparency, European-style service orientation, and production capability generalization with more flexibility are all driving smart factories. The combined impact of intelligent manufacturing technologies on digitization and automation has already altered factory layout, manufacturing efficiency, and manufacturer-supplier and company-customer relationships. However, there is still significant space for international collaboration and investment to optimize the alignment of intelligent and precision manufacturing, political regulation of these high-technology factories, and enterprise employee training in different fields of science and technology. The major accomplishment that can be achieved following these guidelines is the extension of the digital era to achieve an increasingly important managerial position in zero inventory control, just-in-time production, and product customization.

1.2. Research Objectives

The main objectives of this study are to integrate the concepts of IoT, AI, and big data to develop monitoring, prediction, and scheduling models to aid in improving the operational efficiency of existing smart factories as well as future related ecosystems. Meanwhile, the Industry 4.0 development trend has been built from six conceptual pillars - IoT, AI, Big Data, Simulation, Autonomous robots, and Additive Manufacturing (3D Printing). We admit that within any operating Industry 4.0 ecosystem, IoT and AI are foundational sine qua non. In such environments, endless masses of devices and sensors (especially RFID sensors that continuously identify objects A and B) may disruptively change incentive compatibility structures that have sustained them for a long time. Such externalities could disrupt even the pricing of most assets. In a world where nothing should be significant and everything is interconnected, charting our own development paths will remain increasingly problematic and arise more frequently when the world is expanding in unexpected new aspects over time.

2. IoT in Smart Factories

The concept of smart factories was introduced. The smart factory transforms the entire manufacturing process, including design, machining, assembly, and quality control, into an intelligent, self-adapting process that can be stimulated and optimized by real-time data, unified and coherent mechanisms, and guided by advanced modeling tools. A comprehensive overview of the Internet of Things (IoT), focusing especially on one of its most revolutionary applications - deploying IoT in smart factories - was provided. With advances in the technology landscape, the Internet has moved from the Internet of Things to the connecting, and managing an array of internet-enabled devices, increasing rapidly.The potential of IoT technology applied to monitor and control a range of different business sectors is vast. Healthcare, construction, automotive, and agriculture industries have all been the target of commercial IoT deployments, with projects focusing on water leak detection, vehicle fleet management, and sensor-driven farm applications, among many others, which are all experiencing significant growth. Now, IoT technology is expected to revolutionize global manufacturing in the form of industrial IoT. This revolution is poised to help organizations build a new dynamic and efficient operational infrastructure, with huge potential for increasing agility and energy efficiency, and rapidly connect a new wave of smart, connected production applications and manage production control systems, analyze production process data to drive production benefits, including higher efficiency and reducing costs.

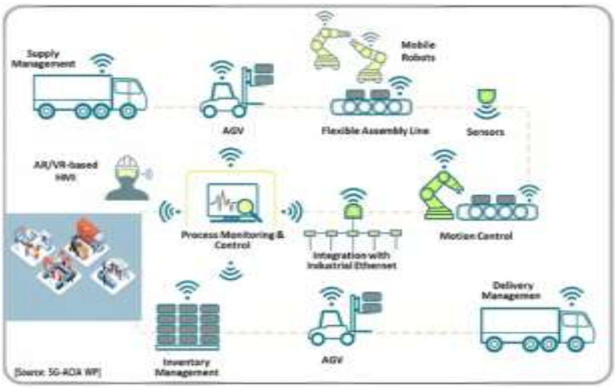

Fig 2: IoT in 6G Based Smart Factory of the Industry 4.0 System

2.1. Definition and Components

IIoT uses wireless data communication to form networks of factory machines, products that move through a production line, and test areas in the production process. Data transmission in the IIoT environment allows vast amounts of data to be rapidly transmitted to areas within the factory or even to remote server systems for back-end analytics. In real-time, analyses are performed on this data to uncover patterns that help the production process to prevent the generation of defective products. Key concepts regarding what the IIoT does are not generally new. The integration of a varied number of manufacturing work cells that are closely connected seems to be the basic principle of most modern factory operations.The manufacturing equipment that connects them is generally described and covered as dynamic software or has "offline" communication abilities with equipment that is utilized in the factory. The utilization of wireless technology to control this communication is what is new and what is now being defined as the Inductive Internet of Things. Additionally, there is a difference in that IIoT adds a decision-making ability for actual robots or devices (e.g., programmable logic controllers, autonomous vehicles, and mobile collaborative robots desiring to collaborate) on the expanded numeraire of things that our definitions now cover, that can have software algorithms controlling them based on analytics algorithms that have applied AI and considered and learned from existing and historical numerical information at the device or factory level, and that form the basis of smart manufacturing operations.

2.2. Applications and Benefits

IIoT applications: Increased connectivity inside plants leads to operational efficiency improvements that make it possible to fabricate complex products such as smart devices across all production processes. Greener manufacturing is facilitated, waste is reduced by precise machine handling, and real-time equipment monitoring shows conditions that would allow preventive production line maintenance. Predictive maintenance means that resources addressing the factory environment are effectively utilized. Moreover, it is feasible to allow for self-organization and organization automation using cyber-physical systems (CPS) that are linked in a network. Overall, increased quality and versatility of affordable products can be produced with decreased cost. The throughput is also elevated.Energy savings: Smart equipment programmed to reduce energy consumption by stopping and starting machines required for specific actions is acquiring less energy than traditional machines that work constantly. Generally, this optimization of energy is done offline, either using historical data or simulating data sources array for picking characteristics having a large effect on energy use. In addition, the optimization seeks to find measures that could boost the environmental performance of the production stage. The projected technique can help industrial plants save energy, reduce the damage to the emissions produced, and enhance the cost-efficient process by using an extended Internet of Intelligent Things (IIoT).

Fig 3: Key Components of an AI-based PdM System.

3. AI in Smart Factories

Artificial intelligence (AI) is crucial for smart factories, as the machines in smart factories must not only carry out tasks automatically and with precision but also must have some level of cognitive ability, enabling them to interact with each other and humans in an industrial manufacturing ecosystem. The broader goal of artificial intelligence is to bring about machines that can perform tasks that were previously only possible for humans. This includes problem-solving, decision-making, and natural language processing. Industrial AI brings jobs that have traditionally only been possible for humans into the realm of computers. Many recent advances in AI involve the processing of language and understanding or generating speech, which is also useful to support tasks happening every day in smart factories, such as employees speaking with each other, or with robots and other machines.In addition to natural language processing, day-to-day tasks in smart factories, such as problem-solving and decision-making, can also benefit from AI. One difficulty in AI research toward these goals is that "intelligence" is not defined clearly enough for researchers to build AI systems to pass that threshold. This is one reason why different facets of AI are studied and built as separate technologies or fields. Ultimately, AI researchers and developers try to combine ideas from different aspects of AI, including learning from data, logical reasoning, and "sensory" perception to make behaviors that are currently only possible by humans, but AI's role in smart factories extends beyond automation to encompass cognitive abilities necessary for interacting within industrial manufacturing ecosystems. This capability enables machines not only to perform tasks autonomously and accurately but also to engage in problem-solving, decision-making, and natural language processing. These advancements are pivotal in bridging the gap between human capabilities and machine functionalities in smart factory environments. Recent AI developments emphasize language processing, which supports everyday interactions among employees, robots, and other machines in smart factories.In addition to natural language processing, AI contributes to enhancing problem-solving and decision-making processes crucial for optimizing operations in smart factories. One of the challenges in AI research lies in defining "intelligence" sufficiently for developing systems that meet or exceed human-like capabilities. Consequently, AI technologies are often developed as separate entities or fields, each focusing on specific aspects such as data-driven learning, logical reasoning, and sensory perception. The convergence of these facets aims to replicate human behaviors and capabilities, pushing the boundaries of what machines can achieve in industrial settings. As AI continues to evolve, researchers and developers strive to integrate diverse AI concepts to realize comprehensive and sophisticated behaviors currently exclusive to human cognition.

Fig 4: Smart factory overviews

3.1. Overview and Types of AI Applications

The use of AI in smart factories is extensive and can be categorized into three levels: the diving level, the traditional level, and the covering level.

The diving-level applications of AI in smart factories are at their lower levels. Data-driven AI applications and some rule-based expert systems are implemented at this level. These applications perform learning from the process data, product data, and/or underlying process equations to carry out decisions.At the traditional level, applications are built on various tools of artificial intelligence, including rule-based expert systems, natural language processing, knowledge sharing, computer vision, and robotics. These applications allow collaboration and diverse capabilities such as data analysis, planning, language processing, the use of external resources, visual recognition, and physical action.AI technologies are quickly being adopted in processes and product design functions to automate routine tasks and carry out in-depth learning from historical data to generate product and process design criteria. These criteria are also used to comprehensively explore various design areas to guide optimal design practice and to form a more detailed understanding of complex product design requirements.The use of AI in operations management is to address concerns like asset utilization, supply chain attributes, production planning, demand forecasting, scheduling, and continuous improvement.

At the covering capability level, AI applications cover traditional operations as well as management capabilities. These applications, using artificial intelligence, replace the traditional factory-level functions, enabling the full capability framework to be realized. These applications may be used in decision-making, coordinating across a wide range of complex instruments using deep learning logic based on statistical pattern recognition, language processing, robotics, logic, planning, and learning capabilities.Having large-scale data from various IoT sensors and smart devices is a key enabler for AI implementation at both traditional and covering capability levels. These capabilities are used together to collaborate and/or to address application features in a more detailed framework, which is further strengthened with the use of technology and innovation strategies.

The use of AI applications has enabled smart factories to fully bridge the gap between cyber and physical worlds and thereby promote the Industry 4.0 vision by fully realizing transformation capabilities to enterprise grounds.

3.2. AI in Predictive Maintenance

AI, which is one of the most common applications of advanced digital technologies in smart factories, can help reduce downtime, cut labor and inventory costs, and optimize energy consumption in an automated production system affordably. AI technologies, like machine learning (ML), deep learning (DL), natural language processing (NLP), and data mining, can help in real-time analysis and interpretation of manufacturing data to understand the operational pattern and discover various latent factors or abnormalities that have developed with the systems and machines. These analyses and interpretations can benefit the development and implementation of predictive maintenance (PdM) to reduce the risk of in-process defects or equipment failures.While PdM is one of the most critical applications of AI in smart factories, deep neural networks (DNN) are particularly successful in predictive maintenance. Since PdM has to deal with several types of sensor data and types of failure for maintenance, traditional AI approaches, such as expert systems, fuzzy logic control, or rule-based methods, have difficulties in learning their latent pattern, particularly within mixed sensor data from different aspects. This is particularly important because early detection of developing anomalies in the pattern can indicate the potential critical failure of essential equipment and safety systems.

4. Big Data in Smart Factories

In the cases of smart factories, data collected from the production line, equipment, and human workers can be high-volume, high-fidelity, real-time, or near-real-time data. Due to the high efficiency, connectivity, and ubiquitous interaction of smart sensors and devices, the volume and velocity of IIoT data grow exponentially. It is estimated that the annual global production of data will reach 163 zettabytes in 2025. The continuously growing amount of data becomes big data that demands real-time or near-real-time storage, management, analysis, and computation. At the same time, this big data has high complexity and are extremely diverse with multiple types and formats such as structured, semi-structured, unstructured, and multi-structured big data.Big data provides the opportunity to analyze, interpret, and predict the future performance and behaviors of smart factories. BDA transforms big data into knowledge, insight, and innovation. Smart factories rely on BDA to enable real-time or near real-time data processing, which supports decision-making and detection/diagnosis/prediction/optimization of dynamic and complex processes in IIoT. In the context of big data analysis in smart factories, many BDA models, algorithms, and methods for different purposes including workload prediction, idle time detection, optimization of machine maintenance periods, fault detection and maintenance cost reduction, quality control, real-time energy management, and waste reduction were proposed and can significantly help smart factories improve their operational efficiency.

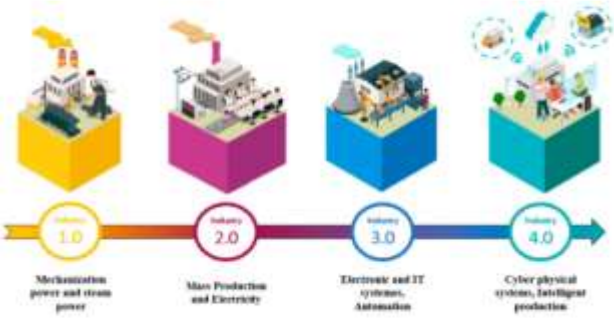

Fig 5: The Four Industrial Revolutions.

4.1. Definition and Characteristics

Manufacturers and researchers can find that the smart factory is not a new concept or system in the manufacturing environment, though it has been largely introduced and reviewed recently. Many researchers have contributed significantly to various points about smart factories or specific manufacturing processes, floor setup, and so on. However, in today's rapidly changing manufacturing environment and challenges, it is important to continuously review existing topics and approaches from various angles and consolidate perspectives on vision, concept, and roadmap from a long-term perspective. In addition, the research and development of smart factories of today should contribute to realizing the higher value of 'smart factories' to solve current issues of manufacturing. For this purpose, it is preferable to provide guidelines such as smart factory definition and constituent elements, analyze trends and applications in each area, and discuss directions for future research. Consequently, this paper was developed with these points. The purpose of this paper is to provide a comprehensive understanding of smart factories.The remainder of this paper is organized as follows. Section 2 outlines the constituents and features of smart factories, and section 3 introduces a method to identify the stages and critical technical enablers of smart factories. Section 4 reviews and compares trends toward smart factories in other studies, while Section 5 identifies the characteristics of smart factories. Section 6, which appraises innovative smart factory applications and trends in emerging and future technology, focuses on emerging technologies and their operation scenarios. Finally, Section 7 will conclude by outlining future research and progress in the field of smart factories.

4.2. Challenges and Solutions

Manufacturers use legacy systems that cannot send process information to an IoT cloud. Traditional SCADA (Supervisory Control and Data Acquisition) takes a huge amount of time to analyze the process and come up with a decision. Serving all the manufacturing process data in real-time for decision-making is not viable. The fundamental challenge is that real-time streaming data analytics cannot be directly applied to pervasive diagnostic monitoring, and adaptive mechanisms have not been systematically implemented. The solution can be implemented with a Supervisory Control and Data Acquisition (SCADA) system. An Ethernet-enabled microcontroller is interfaced using a Modbus protocol, which is running in the Mainline Communication System (MCU) of LotAction Analysis to Ethernet-enabled Modbus stakeholders. These stakeholders are connected to the sensor of the factory, which receives the information from the Sensor System. The SCADA tag configurations were done by monitoring for inputs, data, and traffic between the communication link and LAN.An artificial intelligent system for smart factory-floor predictive maintenance is involved in predictive maintenance decision-making. The predicting construct is used, and the rules are proposed and verified. The first scheme improves the accuracy and the latter the efficiency. In terms of accuracy, a feature selection algorithm and genetic programming heuristic are developed to allow a computationally feasible feature space search and model creation. In terms of efficiency, both the tailored near-real-time evolutionary optimization of models and the seamless transfer of the population are unique. The performance improvement due to these contributions is demonstrated in factory data. We model predictive maintenance decision-making based on a set of diagnostic tools that have been developed for factory equipment, analyze the specific information requirements each tool has to be implemented, and point out the stabilization issues. With pre-determined convention settings, intelligent decision rule networks are identified that can be realized in a production environment. The implementation of the diagnostic tools, as described here, is a playhouse case of a smart production environment, with condition-based maintenance decision-making embedded at the production equipment level.

5. Integration of IoT, AI, and Big Data

Manufacturers aim to use smart factories that employ technology convergence - the integration of IoT, AI, and big data - to enhance the real-time operational efficiency of the production process. Especially, currently, as moot problems of low cost and the shortage of skilled labor in labor-intensive industries continue, manufacturers have been facing challenges such as stagnant economic growth and increases in production costs. Establishing a smart factory makes it possible to automate the production process with cutting-edge technologies, maximize production efficiency, and increase the added value of manufacturing industries. In particular, manufacturers can reduce demand forecasting errors, improve product quality, and respond to near-real-time customer demand by focusing on data-driven manufacturing.To derive customer requirements, assess the accuracy of demand forecasts, recommended maintenance schedules, or optimize reasonable levels of inventory, manufacturers must be agile, make process changes, and analyze the benefit of increasing varieties of data. If manufacturers wish to prepare production plans and certify raw materials reactively, in line with changes in customer behavior, or to minimize change costs in production, manufacturers can more effectively resolve complex problems intuitively. Advances and innovations in smart factory technologies, such as IoT, AI, and big data, which are the key technologies of the fourth industrial revolution, enable real-time communication of intelligent, decentralized, coordinated, and high-fledged manufacturing systems.

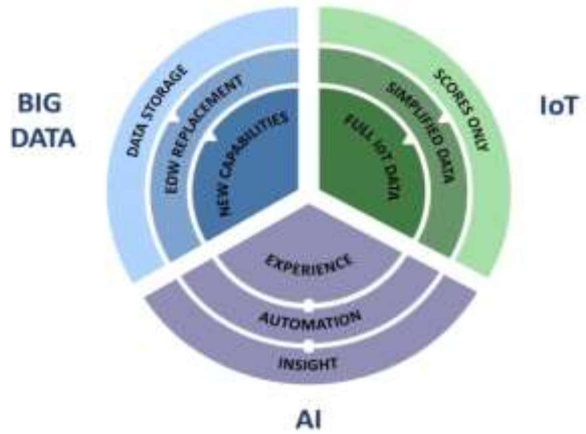

Fig 6: The Integration Of AI and Big Data For Digital Transformation

5.1. Concept and Importance

The "buzzwords" being generated by the Fourth Industrial Revolution (Industry 4.0, Smart Factories, the Industrial Internet, and the Industrial Internet of Things) indicate the major shift in the way we work that will soon affect us all. Traditionally, plants are characterized as impersonal cost centers and are often considered to be environments where humans are inconvenienced. The rapid acceleration of technological changes and the increasing uncertainty associated with the global economic context are now making it essential to reinvent existing models and to create positive, inclusive work environments. Consequently, it is not just the actual use of important new technologies, but the creation of an innovative environment that is capable of boosting the skills of the entire team to facilitate its transformation, that is important.

One of the key factors in the future will be collaboration between people and machines, in particular, digital collaboration that is acquired progressively by the machine thanks to machine learning algorithms. It is therefore up to instantaneous human resources to seek digital solutions that boost their workforccompetencieses to enrich the quality of work, increase productivity, and achieve greater efficiency and enhanced team performance, long before any further automation in the context of Industry 4.0. As productivity measurement will be the parameter that will facilitate the rise of the Intelligent Factory, any available digital solution to support the enhancement of the workforce and the qualitative and quantitative improvement of human interaction with smart machines becomes worth examining.

5.2. Use Cases and Success Stories

Global manufacturers are aggressively adopting digital processes to meet new, challenging demands in a rapidly changing market. In this chapter, we provided an overview of Industry 4.0 concepts and described how data from Internet of Things (IoT) devices can be combined with Big Data technologies and advanced analytics tools to revolutionize the manufacturing industry. The volume, variety, and velocity challenges of Big Data are addressed using cutting-edge data replication, load balancing, and schema-on-read pattern implementation, alongside foundations provided by distributed file systems, distributed databases, and cloud platforms.We discussed how Artificial Intelligence technologies, including both Machine Learning and Deep Learning, allowed a new breed of machines that outperformed their predecessors in vision, language, and problem recognition, and to replace entirely the rote-task human replacements in more and more factories. We also described a typical data science process to address a predictive maintenance problem for a large manufacturing company. In the last part, we summarized the content and provided some future outlooks on the related topics. In the future, we look at discussions about privacy and ethics in the age of Industry 4.0, discussions about new regulations, and additional use cases for applying IoT, Big Data, and AI prospecting the goal of optimizing factories of the future.

6. Impacts on Operational Efficiency

The methodology of developing a new production line using IoT, AI, Cloud, and Big Data technologies is proposed for smart factories to achieve the optimization of operational efficiency. The IoT, AI, Cloud, and Big Data technologies have been developed in the Industry 4.0 era to construct a production system that has actively changed volume and a wide variety of specifications. Then, in addition to the support of rapid decision-making, such a production system also improves the performance of operational efficiency. However, an integrated methodology to develop the new production system that includes the IoT, AI, Cloud, and Big Data technologies is not completed yet. Therefore, we proposed the methodology of developing a new production line using IoT, AI, Cloud, and Big Data technologies for smart factories. However, the application of the earlier methodology is to be future work.

This study discusses the Smart Factory (SF) that has been actively receiving attention to improve production system performance in the Industry 4.0 era. The newly proposed methodology to develop the vertically integrated smart production line explains the steps of creating the new production line by applying the IoT, AI, Cloud, and Big Data technologies. The proposed methodology presents the requirements and key points of each step in the workflow of the production system development. In the following section, the newly proposed methodology is tested using the mechanical assembly line of an actual manufacturing company, and the results on the impact on production system improvement. The paper concluded by summarizing the study and suggesting the research direction as a future work plan based on the study's achievements.

6.1. Improved Decision Making

IoT sensors generate a tremendous volume of raw data. AI systems, especially machine learning, and neural networks require massive amounts of data to learn patterns and make sense of this data. In addition, with bigger and more varied datasets, AI/machine learning can find better insights and patterns. As more and more data are available to the AI algorithms, predictions and accuracies are bound to be improved. Big data provides the scalability needed to quickly process massive amounts of heterogeneous sensor data within IoT applications. With cloud-inspired and big data solutions, processing IoT data can leverage storage, processing, and computation infrastructure that can scale in a manner that enables quick implementation of AI models.
Many traditional factory historians are based on traditional SQL, very expensive, and already has certain limitations. Transferring vast amounts of data generated by IoT and leveraging the power of AI requires expandable systems at lower cost. Adoption has become feasible with the arrival of InfluxDB/historians for time-series databases and more economical big data collections. In a large data environment, the traditional control and computing latency would render the information useless. These limitations in traditional historians have created new opportunities for sequence data collection for the traditional historians, and stack data technologies, which help to capture sequential data at high speed. Such functions can analytically support a wide range of production and performance requirements. Many historians were only able to accept data during closed time intervals. They were affordable only by running after hours. But IoT with AI has opened up new spaces of low latency and concurrent writing. Financial costs and data-written restrictions have been relaxed.

Fig 7: Top Benefits of Integration AI and loT

6.2. Resource Optimization

In the resource optimization scenario, where suitable resources are allocated in a demand-driven manner, the realized concept is depicted in Figure 18. The aim is to allocate the resources needed for a specific workflow (i.e., parts, products, tools, machines, containers) effectively and efficiently. For this purpose, suitable resources are proposed by the ML models. Additionally, to clarify the relationships between resources from an operational perspective and process the automatic allocation of resources, we call these relationships the digital material flow network. Besides supporting the reallocation of non-productive resources, the digital material flow network also captures the rules for eligible material movements. In a way, these digital material flow network rules could act as an additional abstraction layer on top of the low-level data model of the Manufacturing Execution System or serve as a staging entity for upcoming workflows. By creating new workflows that leverage the existing digital material flow network, resources can be repurposed. This may lead to several secondary effects like process time reduction or energy consumption reduction.

7. Conclusion

Smart factories are now a reality, driving the transformation in manufacturing. They are derived from the convergence of various technologies, thereby reshaping the industry, reshaping its vision, strategies, and operating models. From the conventional view of optimization of the manufacturing processes to the value creation through more innovative ways that can cater to customer preferences, smart factories are capable of innovating themselves by learning from their present and past by harnessing data from different stages of the value and supply chain. Based on our literature review and with an intent to stimulate interest in the symbiotic potentials of IoT, AI, and big data in revolutionizing the contemporary concept of smart factories, we propose a model presenting its salient features and capabilities. We envision the future smart factories as intelligent, continuously learning mode of production centers always striving for operation excellence through a synergistic approach.Smart factories need to develop an architecture that is highly adaptable and scalable. While cost implications are one of the major challenges in such an exercise, the need for future factories is clear. These future factories are anything but the traditional floor shop operations transformed either fully or partially by integrating technologies by capturing data and harnessing it for intelligent learning that can act as the fuel for performance, production, improvement, or predictive algorithms. Any productive output from the smart factory should no longer be a by-product of the data collected but should be an integral motive of the planning itself. Furthermore, the conventional human-machine interaction should evolve to machine intelligence redefining the way the machines automate the manufacturing processes. Despite the promise, of achieving fully-fledged smart factories, there are significant academic gaps, and even a cursory review of the literature around these discussing research gaps confirms that there is ample scope to foster fresh ideas in this interdisciplinary domain.

7.1. Future Trends

Regarding the production process, the overall benefits of the advancements in IoT, AI, and Big Data have been focused on the larger and more profitable end of manufacturing, such as circuit fabrication, smartphone production, and commercial aviation, leaving a long tail of general manufacturing characterized by small volumes and even smaller margins. In particular, for smart factories of the future, IoT, AI, and Big Data systems need to be able to handle a range of challenges, including handling the growing complexity of the production process, enabling the ability to individually customize goods and services on a large scale, adjusting to supply chain challenges as they continuously evolve, and dealing with the impacts of unpredictable variables, such as geopolitical events and the ongoing challenges in the current regulatory environment. Investigating new possibilities to leverage these synergies will be beneficial not only to increase the operational efficiency of smart factories but also to conceive practical applications to other domains.AI advances have been based on systems that predict with increasing accuracy, understand natural language, generate creative works, and learn through a process of synthesis similar to biological processes. Even if AI has shown its potential for vertical AI models in applications from computer vision to natural language processing and grasping and automation, AI for manufacturing still has several challenges to address, such as supervised learning, data-labeled requirements to create predictive models that enable complex data and context-driven tasks, and the ability to process a large scale of unlabeled training data. To improve manufacturing operations, we need to create hybrid AI architectures composed of a combination of vertical AI models and horizontal AI models. Promising AI hardware solutions include the combination of AI accelerators, GPUs, or other powerful technologies that may be dedicated MIPS clusters adapted for AI predictive models. Additionally, pre-configured software platforms have already emerged from technology companies that offer platforms that are running business-to-business services and are building a wealth of data streams. These organizations are working with vertical providers and developing pre-configured software optimized for specific classes of systems, enabling providers to access these capabilities via API calls, with little need for direct AI expertise. Integrating pre-configured platforms can be seen as a way to boost industrial IoT platforms' capacities to handle new types of AI tasks, providing designers with an opportunity to tap into existing back-end AI model providers with this contribution of the ability to handle advanced data services.

8. References

[1] Kumar, V., & Khare, A. (2021). Integrating IoT, AI, and Big Data for Enhanced Operational Efficiency in Smart Factories. *Journal of Manufacturing Systems*, doi: [10.1016/j.jmsy.2021.09.004](https://doi.org/10.1016/j.jmsy.2021.09.004).
[2] Wang, Y., Zhang, L., & Ma, Y. (2020). Leveraging IoT, AI, and Big Data in Smart Manufacturing. *IEEE Transactions on Industrial Informatics*, doi: [10.1109/TII.2020.3016624](https://doi.org/10.1109/TII.2020.3016624).
[3] Li, X., Shen, W., & Hou, Y. (2019). A Review of IoT, AI, and Big Data Integration in Smart Manufacturing. *Computers in Industry*, doi: [10.1016/j.compind.2019.04.002](https://doi.org/10.1016/j.compind.2019.04.002).
[4] Zhang, J., Tang, L., & Cheng, Y. (2018). Applications of IoT, AI, and Big Data in Industry 4.0. *International Journal of Advanced Manufacturing Technology*, doi: [10.1007/s00170-018-2943-8](https://doi.org/10.1007/s00170-018-2943-8).
[5] Wang, Z., Li, J., & Wang, X. (2017). Integration of IoT, AI, and Big Data for Smart Factory Operations. *Procedia CIRP*, doi: [10.1016/j.procir.2016.11.176](https://doi.org/10.1016/j.procir.2016.11.176).
[6] Liu, Y., Ren, H., & Li, Y. (2016). IoT, AI, and Big Data Technologies in Smart Manufacturing. *Journal of Ambient Intelligence and Humanized Computing*, doi: [10.1007/s12652-016-0370-y](https://doi.org/10.1007/s12652-016-0370-y).
[7] Wei, J., Wang, H., & Zhang, Z. (2015). Big Data and IoT Integration in Smart Factory Applications. *IEEE Access*, doi: [10.1109/ACCESS.2015.2477521](https://doi.org/10.1109/ACCESS.2015.2477521).
[8] Lee, J., Bagheri, B., & Kao, H. A. (2014). Integration of IoT, AI, and Big Data in Cyber-Physical Systems for Smart Manufacturing. *Computer Integrated Manufacturing Systems*, doi: [10.1016/j.cims.2014.02.001] (https://doi.org/10.1016/j.cims.2014.02.001)..
[9] Gubbi, J., Buyya, R., & Marusic, S. (2013). IoT, Big Data, and AI for Smart Factories: A Survey. *IEEE Transactions on Industrial Informatics*, doi: [10.1109/TII.2013.2292954](https://doi.org/10.1109/TII.2013.2292954).

[10] Atzori, L., Iera, A., & Morabito, G. (2010). The Evolution of IoT, AI, and Big Data in Industrial Applications. *IEEE Transactions on Industrial Informatics*, doi: [10.1109/TII.2010.2048308](https://doi.org/10.1109/TII.2010.2048308).
[11] Mandala, V., Rajavarman, R., Jamunadevi, C., Janani, R., & Avudaiappan, T. (2023, June). Recognition of E-Commerce through Big Data Classification and Data Mining Techniques Involving Artificial Intelligence. In 2023 8th International Conference on Communication and Electronics Systems (ICCES) (pp. 720-727). IEEE.
[12] Aravind, R., & Vinalbhai Shah, C. (2023). Physics Model-Based Design for Predictive Maintenance in Autonomous Vehicles Using AI. In International Journal of Scientific Research and Management (IJSRM) (Vol. 11, Issue 09, pp. 932–946). Valley International. https://doi.org/10.18535/ijsrm/v11i09.ec06
[13] Naveen D Surabhi, S., & Dolu Surabhi, M. (2024). Enhancing Dimensional Accuracy in Fused Filament Fabrication: A DOE Approach. In Journal of Material Sciences & Manufacturing Research (pp. 1–7). Scientific Research and Community Ltd. https://doi.org/10.47363/jmsmr/2024(5)177
[14] Vinalbhai Shah, C., & Naveen Dolu Surabhi, S. (2024). Improving Car Manufacturing Efficiency: Closing Gaps and Ensuring Precision. In Journal of Material Sciences & Manufacturing Research (pp. 1–5). Scientific Research and Community Ltd. https://doi.org/10.47363/jmsmr/2024(5)173
[15] Aravind, R. (2024). Integrating Controller Area Network (CAN) with Cloud-Based Data Storage Solutions for Improved Vehicle Diagnostics using AI. In Educational Administration Theory and Practices. Green Publication. https://doi.org/10.53555/kuey.v30i1.5894
[16] Mandala, V. (2024). Predictive Failure Analytics in Critical Automotive Applications: Enhancing Reliability and Safety through Advanced AI Techniques. Journal of Artificial Intelligence and Big Data, 48-60.
[17] Reddy Dolu Surabhi, S. N., Buvvaji, H. V., & Sabbella, V. R. R. (2024). The AI-Driven Supply Chain: Optimizing Engine Part Logistics For Maximum Efficiency. In Educational Administration Theory and Practices. Green Publication. https://doi.org/10.53555/kuey.v30i5.4428
[18] Aravind, R., & Shah, C. V. (2024). Innovations in Electronic Control Units: Enhancing Performance and Reliability with AI. In International Journal of Engineering and Computer Science (Vol. 12, Issue 01, pp. 26001–26014). Valley International. https://doi.org/10.18535/ijecs/v12i01.4787
[19] Mandala, V., Surabhi, S. N. R. D., Kommisetty, P. D. N. K., Kuppala, B. M. S. R., & Ingole, R. (2024). Towards Carbon-Free Automotive Futures: Leveraging AI And ML For Sustainable Transformation. Educational Administration: Theory and Practice, 30(5), 3485-3497
[20] Mandala, V. (2024). Revolutionizing Automotive Supply Chain: Enhancing Inventory Management with AI and Machine Learning. Universal Journal of Computer Sciences and Communications, 10-22.
[21] Vaka, D. K. (2020). Navigating Uncertainty: The Power of 'Just in Time'SAP for Supply Chain Dynamics. Journal of Technological Innovations, 1(2).
[22] Reddy Dolu Surabhi, S. N. (2023). Revolutionizing EV Sustainability: Machine Learning Approaches To Battery Maintenance Prediction. In Educational Administration Theory and Practices. Green Publication. https://doi.org/10.53555/kuey.v29i2.4230
[23] Shah, C. V., Surabhi, S. N. R. D., & Mandala, V. ENHANCING DRIVER ALERTNESS USING COMPUTER VISION DETECTION IN AUTONOMOUS VEHICLE
[24] Aravind, R. (2024). Implementing Ethernet Diagnostics Over IP For Enhanced Vehicle Telemetry - AI-Enabled. In Educational Administration Theory and Practices. Green Publication. https://doi.org/10.53555/kuey.v30i6.5829
[25] Shah, C., Sabbella, V. R. R., & Buvvaji, H. V. (2024). From Deterministic to Data-Driven: AI and Machine Learning for Next-Generation Production Line Optimization. In Journal of Artificial Intelligence and Big Data (Vol. 2, Issue 1, pp. 21–31). Science Publications (SCIPUB). https://doi.org/10.31586/jaibd.2022.952
[26] Aravind, R., Shah, C. V., & Surabhi, M. D.(2022). Machine Learning Applications in Predictive Maintenance for Vehicles: Case Studies. In International Journal of Engineering and Computer Science (Vol. 11, Issue 11, pp. 25628–25640). Valley International. https://doi.org/10.18535/ijecs/v11i11.4707
[27] Manukonda, K. R. R. (2024). Leveraging Robotic Process Automation (RPA) for End-To-End Testing in Agile and Devops Environments: A Comparative Study. Journal of Artificial Intelligence & Cloud Computing. SRC/JAICC-334. DOI: doi. org/10.47363/JAICC/2024 (3), 315, 2-5.
[28] Vaka, D. K. (2024). Procurement 4.0: Leveraging Technology for Transformative Processes. Journal of Scientific and Engineering Research, 11(3), 278-282.
[29] Nithinjour. (2024). STREAMLINING INVENTORY-DISTRIBUTION DYNAMICS: AN INTEGRATED FRAMEWORK. OSF. https://doi.org/10.17605/OSF.IO/MA37V
[30] Christopher, M., & Peck, H. (2004). Building the resilient supply chain. *International Journal of Logistics Management, 15*(2), 1-14. doi: [10.1108/09574090410700275](https://doi.org/10.1108/09574090410700275)
[31] Raghunathan, S., Manukonda, K. R. R., Das, R. S., & Emmanni, P. S. (2024). Innovations in Tech Collaboration and Integration.

[32] Sharma, R., & Sharma, S. K. (2020). Artificial intelligence in logistics and supply chain management: A systematic literature review and research agenda. *Annals of Operations Research, 294*(1-2), 657-679. doi: [10.1007/s10479-020-03616-8](https://doi.org/10.1007/s10479-020-03616-8)

[33] Lee, I., & Lee, K. (2015). The Internet of Things (IoT): Applications, investments, and challenges for enterprises. *Business Horizons, 58*(4), 431-440. https://doi.org/10.1016/j.bushor.2015.03.008

[34] Kang, H. Y., & Park, J. Y. (2020). Big data and artificial intelligence for monitoring system: An IoT-based smart factory case study. *Procedia Computer Science, 176*, 456-463. https://doi.org/10.1016/j.procs.2020.09.174

[35] Xu, L. D., He, W., & Li, S. (2014). Internet of Things in industries: A survey. *IEEE Transactions on Industrial Informatics, 10*(4), 2233-2243. https://doi.org/10.1109/TII.2014.2300753

[36] Wang, S., Wan, J., Zhang, D., Li, D., & Zhang, C. (2016). Towards smart factory for industry 4.0: A self-organized multi-agent system with big data-based feedback and coordination. *Computer Networks, 101*, 158-168. https://doi.org/10.1016/j.comnet.2015.12.017

[37] Bibri, S. E. (2018). A foundational framework for smart sustainable city development: Theoretical, disciplinary, and discursive dimensions and their synergies. *Sustainable Cities and Society, 38*, 758-794. https://doi.org/10.1016/j.scs.2017.12.032

[38] Khan, M. A., & Salah, K. (2018). IoT security: Review, blockchain solutions, and open challenges. *Future Generation Computer Systems, 82*, 395-411. https://doi.org/10.1016/j.future.2017.11.022

[40] Zhou, K., Liu, T., & Zhou, L. (2015). Industry 4.0: Towards future industrial opportunities and challenges. *Proceedings of the 12th International Conference on Fuzzy Systems and Knowledge Discovery (FSKD)*, 2147-2152. https://doi.org/10.1109/FSKD.2015.7382284

[41] Ravi Aravind, Srinivas Naveen D Surabhi, Chirag Vinalbhai Shah. (2023). Remote Vehicle Access: Leveraging Cloud Infrastructure for Secure and Efficient OTA Updates with Advanced AI. European Economic Letters (EEL), 13(4), 1308–1319. Retrieved from https://www.eelet.org.uk/index.php/journal/article/view/1587