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IoT-Based Automation of Production Planning and Control

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Abstract: The article identifies IoT applications that support production planning and control tasks, enhancing the speed and accuracy of decision-making. The IoT is a network of devices containing electronic components, software, sensors, actuators, and connectivity that enable these objects to connect, interact, and exchange data. It involves technologies such as Wi-Fi, Bluetooth, and Radio Frequency Identification (RFID). Through a PRISMA-compliant systematic review and cluster identification using VOSViewer, a high prevalence of IoT technology interrelated with Production Planning and Control is identified. It is evident that the static planning approach is inefficient because it does not consider dynamic factors such as the arrival of new orders and real-world probabilistic and stochastic issues such as order delays or machine failures. The conclusion is that IoT technology enables real-time monitoring of different processes through sensors, facilitating planning and control in manufacturing processes.

Keywords: *Internet of Things (IoT), Production Planning and Control (PPC), Smart Manufacturing, Real-Time Data Analytics*

1. Introduction

The Internet of Things (IoT) and cloud computing have been receiving a lot of attention lately because they can offer a new approach to intelligent sensing and connectivity—between people, between people and machines, and between machines—as well as on-demand use and efficient sharing of resources [1].

Manufacturing processes are already part of a concept known as Industry 5.0. In this environment, MES (Manufacturing Execution System) and MRP (Material Requirements Planning) platforms are evolving to enable real-time data monitoring, with data available from sensors in various applications; when aligned with planning and control objectives, these platforms play a key role in smart manufacturing.

Real-time data, collected by tools capable of communicating with one another via the Internet of Things (IoT), improves production control, especially in dynamic production environments [2].

In manufacturing operations, sensor technology makes it possible to track production orders, control machines and operators, monitor productivity and efficiency, and ensure traceability throughout the entire process. Real-time monitoring and control of company assets support better planning of maintenance tasks, utilizing the predictive capabilities built into artificial intelligence tools to improve planning and reduce operational losses caused by unexpected downtime and corrective actions.

This article identifies IoT applications that support production planning and control tasks, enhancing the speed and accuracy of decision-making. Production control is an essential component of the production system used to monitor and manage production orders [3].

Furthermore, the availability of real-time data reduces wasted time and enables instant information gathering, facilitating adjustments to the production flow.

2. Theoretical Framework

This section will describe the basic concepts that guided this research.

2.1 IoT devices

The IoT is a network of devices that contain electronic components, software, sensors, actuators, and connectivity, enabling these objects to connect, interact, and exchange data. It involves technologies such as Wi-Fi, Bluetooth, and Radio Frequency Identification (RFID). The Internet of Things (IoT) can be defined as a set of technologies—ranging from Wireless Sensor Networks (WSN) to Radio Frequency Identification (RFID) that enable detection, actuation, and communication via the Internet. [2, 4]

According to [5], the IoT can be defined as an extension of a broad network, providing network connectivity and computational capacity to objects, devices, and sensors with minimal human intervention to generate, exchange, and consume data. In industry, the IoT plays a crucial role in optimizing processes through real-time data collection, enhances machine-to-machine communication, and offers new opportunities to increase efficiency and productivity.

The IoT enables the remote collection, analysis, and management of data. It features three functionally important elements of the IIoT (Industrial Internet of Things): blockchain technology, AI, and 6G. Blockchain is a distributed ledger in which all blocks are linked and can coordinate and track transactions and can be saved to all devices in the IIoT [6]. 6G technology has improved wireless communication, offering low latency in data transfer and seamless connectivity, thereby facilitating the fast cloud computing required for the integration of the IIoT with blockchain technology [7]. Regarding AI, most codes are generic and can be implemented for logistics and transportation vehicles without significant variation or modification. The greater the volume of data fed into the AI algorithm, the higher the probability of achieving accuracy and precision in decision-making [8].

The IoT is crucial for digitizing physical activities and enabling intelligent observation through human-machine, human-human, and machine-machine interactions. The IoT cannot achieve its primary goal of aiding decision-making to improve performance in physical systems without data science capabilities [9].

According to [10], IoT technology involves communication between objects, sensors, devices, controllers, etc., which have the potential to collect data and control or communicate remotely. This information network connects things to things, things to people, and people to people through various communication technologies, such as Wireless Sensor Networks (WSN), Radio Frequency Identification (RFID), Near Field Communication (NFC), Long-Term Evolution (LTE), Long Range (LoRa), Wi-Fi, Bluetooth, Zigbee, etc.

The IoT architecture discussed in [11] is described by four layers: the perception layer, the transport layer, the processing layer, and the application layer. The perception layer includes sensors for measuring and collecting real-time and partially processed data, and the network connection for the sensors is provided by a WSN (Wireless Sensor Network), a collection of sensor nodes organized into a common network with the advantages of being wireless and low-cost, which enables rapid data transmission. The transport layer transfers data from the sensors in the perception layer to the processing layer and vice versa, using a communication protocol. The processing layer stores, processes, and analyzes the data received from the transport layer. The application layer provides user-specific services.

The substantial number of different sensors ensures a constant flow of data on all processes relevant to production, for processing in embedded computer systems. The processed data then triggers corresponding actions in the physical world [12]. Each processing step and action in the physical world also represents a trigger event in the cyber world.

2.2 Production Planning and Control

Production is the transformation of natural resources into value-added products or services to meet consumer needs [2].

Due to rapid market changes and the diversification demanded by customers, product manufacturing models have gradually shifted toward “small-volume/multi-variety” and “short-lead-time” production methods. The production line must quickly switch between the necessary raw materials and product models, and operators must be changed frequently due to the pressure of tight delivery deadlines [13].

[14] describe planning as the scheduling of plant activities at the operational level (day, hour, minute, etc.). During production planning, various performance criteria must be considered, such as on-time delivery, reduction of time spent in the system, and maximization of machine utilization rates.

The static planning approach is inefficient because it does not take into account dynamic factors such as the arrival of new orders and real-world probabilistic and stochastic problems such as order postponements or machine failures [15].

Planning rules can be defined using the following heuristics: finish-earlier/finish-later, minimum/maximum float, minimum free intervals, and minimum delay. In addition, rules can be defined according to shop floor conditions and grouped into three classes: task-based rules (delivery date, process time, deadlines), shop floor-based rules (machines scheduling their own resources), and hybrid rules [16, 2].

The shortest processing time rule specifies that the priority value is the processing time at the workstation. Among the jobs waiting in the queue, the job with the shortest processing time in the queue is selected as the job to be processed first. Under the nearest due date rule, the priority value is the due date. Under the shortest lead time rule, the priority value is obtained by subtracting the total processing time from the time remaining until the due date. Among the jobs waiting in the queue, the job with the lowest priority value in the queue is selected to be processed first. Finally, there is the priority index rule, where the priority value is obtained by dividing the time remaining until the due date by the total remaining processing time. Among the tasks waiting in the queue, the task with the lowest priority value in the queue is selected as the task to be processed first.

[17] propose the next-in-line workload rule (WinQ). This rule determines a task’s priority value based on the conditions of the production line. Under this rule, the priority value is obtained by considering the total processing times of all tasks at the next workstation, depending on the task’s route. Among the tasks waiting in the current queue, the task with the lowest priority value is selected as the next one to be processed. They reported that using this rule minimizes the average throughput time.

3. Materials and Methods

This study is limited to the broad application of IoT in production planning and control across different types of businesses and does not cover specific details regarding the protocols or technologies used. It will not address hardware-specific details but rather the role of IoT in improving production planning and control. The dataset used covers the period from 2015 to 2025.

The approach will examine how IoT was applied and which identified variables supported the production planning and control process. To this end, a PRISMA-compliant systematic review process was applied, consisting of the following steps: identification, screening, eligibility assessment, and inclusion.

In the identification process, the search term “Blockchain OR IoT AND Production Planning OR Production Control” was applied, using filters that included articles, conference papers, and scientific journals published since 2010 in three databases: Scopus, Web of Science, and ScienceDirect.

In the Scopus database, the following filters were applied, resulting in 2,430 articles included in the identification phase:

> (TITLE-ABS-KEY (BLOCKCHAIN) OR TITLE-ABS-KEY (IOT) AND TITLE-ABS-KEY (PRODUCTION PLANNING) OR TITLA-ABS-KEY (PRODUCTION CONTROL)) AND (LIMIT-TO (LANGUAGE , "English")) AND (LIMIT-TO (DOCTYPE , "ar") OR LIMIT-TO (DOCTYPE , "cp")) AND (LIMIT-TO (EXACTKEYWORD , "Production Control") OR LIMIT-TO (EXACTKEYWORD , “Iot”) OR LIMIT-TO (EXACTKEYWORD , "Internet of Things")) AND PUBYEAR > 2010 AND PUBYEAR < 2025

In the Web of Science database, the following filters were applied, resulting in 163 articles included in the identification phase:

> Refine results for Blockchain AND IoT AND Planning (Topic) and Article (Document Types) and English (Languages) Blockchain (OR-Search within topic) and Review Article (Document Types) and 2018 or 2019 or 2020 or 2021 or 2022 or 2023 or 2024 or 2025 or 2026 (Publication Years)

The same filters applied to the Scopus database were extended to ScienceDirect, resulting in 279 articles; when added to the others, this brought the total number of articles identified for this study to 2,872.

The selection of articles for the study was carried out through an analysis of the database with the assistance of the following applications: Mendeley Reference Manager and VosViewer. The bibliographic data were compiled into an Excel spreadsheet, where graphs were generated for bibliometric analysis.

The initial screening process was conducted using Mendeley Reference Manager, where 1,169 duplicate records were eliminated directly within the tool.

Only publications in English were considered due to their scientific relevance and acceptance.

As part of the screening process, a RIS extension list was generated and exported to the VOSViewer application to identify relevant themes in conjunction with the production planning and control process. The following parameters were selected for generating density and network plots: creating maps based on bibliographic data, reading data from reference management files, selecting the “ris” file extension, analyzing keyword co-occurrence and fractional counts, with a minimum of 10 occurrences and 178 keywords.

By applying a Thesaurus filter, we identified the keywords with the highest frequency and link strength, thereby confirming the relevance of IoT and Blockchain in contemporary articles addressing production planning and control.

Keywords	Occurrences	Total Strenght of the link
IoT	875	794
Blockchain	428	369
Industry	368	334
Digital-Applications	403	328
Smart-Application	340	313
Sustainability	280	257

Table 01 – Resumo Thesaurus (VosViewer)

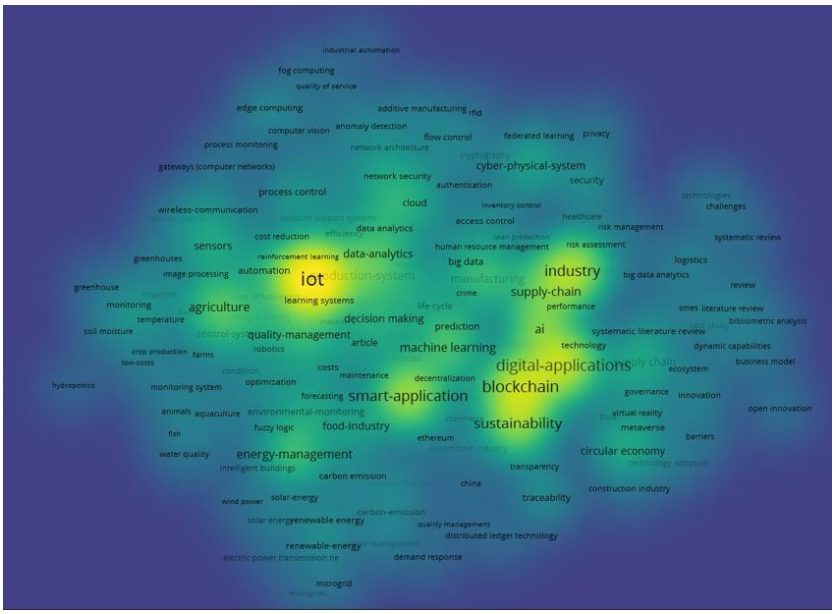


Figure 01 – Density (VosViewer)

In Figure 1, a density plot generated by the VosViewer tool shows the clusters with the greatest impact after applying the filters. The greater the number of neighboring items and the greater the weight of those items, the more yellow the corresponding point appears. Conversely, points of lesser significance are shown in blue.

Six clusters can be identified, as described in the table: IoT, blockchain, industry, digital applications, smart applications, and sustainability.

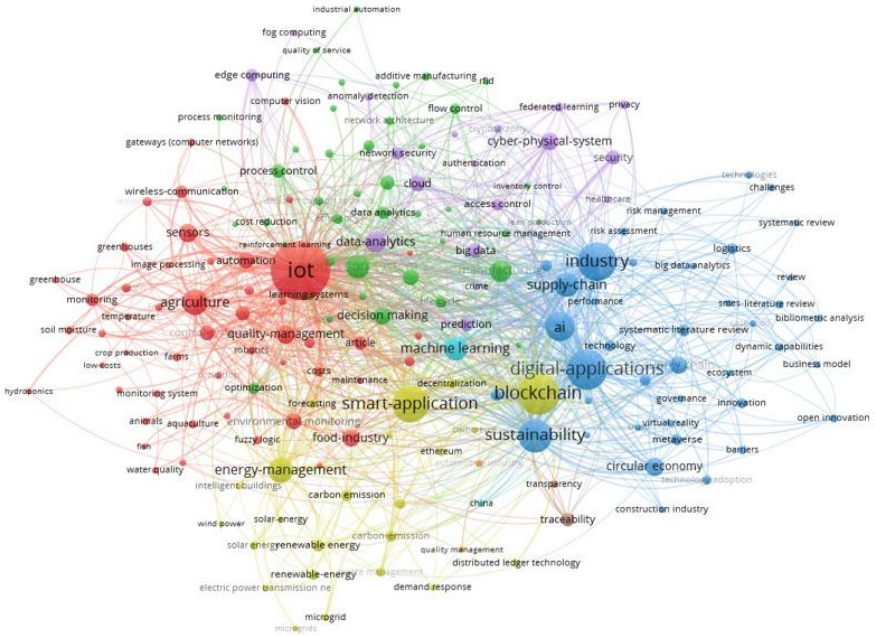


Figure 02 – Network (VosViewer)

Figure 2 shows the network graph created using the VosViewer tool, where items are represented by labeled circles. An item's weight is represented by the size of the circle and its label. The greater the item's weight, the larger the circle and its label. The color indicates which cluster the respective item belongs to. The lines between the items represent connections (links). We observe that the IoT (Internet of Things) item stands out in the upper-left quadrant within the red cluster, and its correlation with all other clusters identified in the analysis is evident.

During the inclusion process, the filter "Blockchain and IoT and Planning Process and Control Process" was applied in the Mendeley manager, and 30 articles were selected for the literature review. The general systematic review process is summarized below in Figure 3.

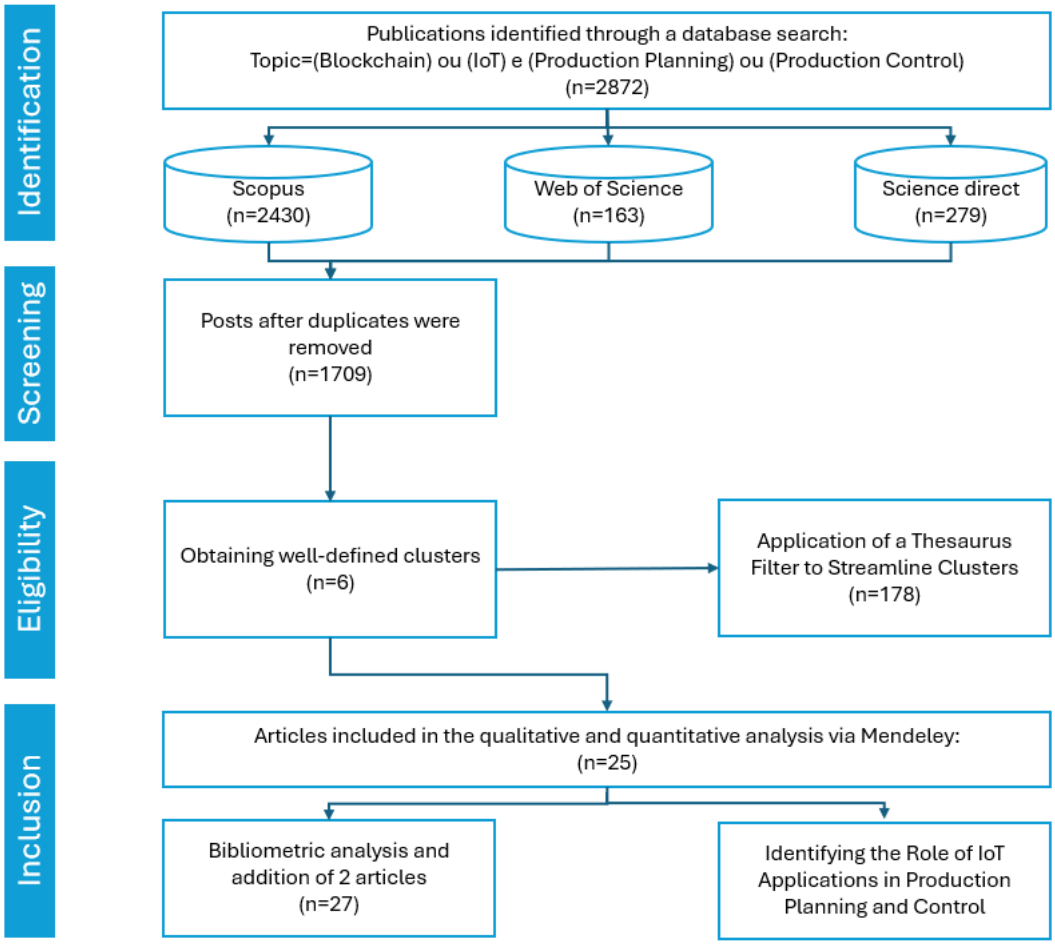


Figure 3 – PRISMA

By compiling the bibliometric data into an Excel spreadsheet, we obtained the results shown in the following graphs, which reveal a significant increase in publications over the last five years regarding the application of IoT systems in production environments aimed at optimizing and automating production planning and control. This is an expected indicator resulting from the strong development and penetration of IoT technologies in production planning and control processes.

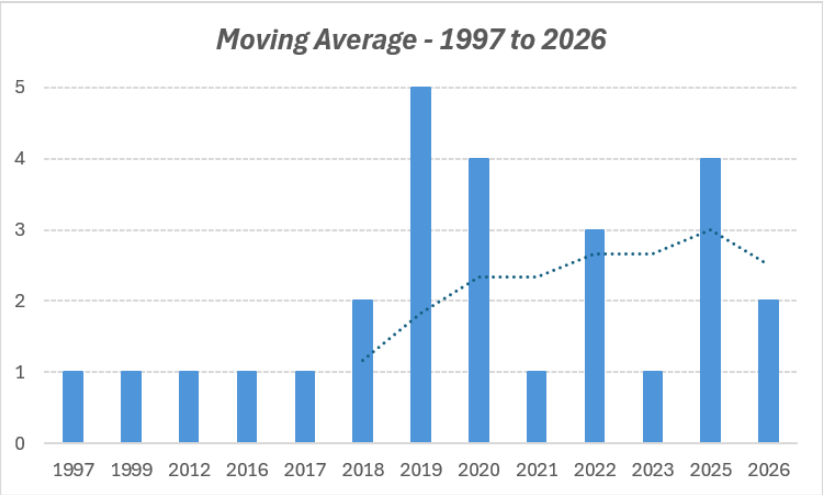


Figure 4 – Articles/year – Source: the author

The filter for the most relevant sources of information lists Elsevier as the publisher with the highest number of articles, followed by MDPI, IEEE, and Springer.

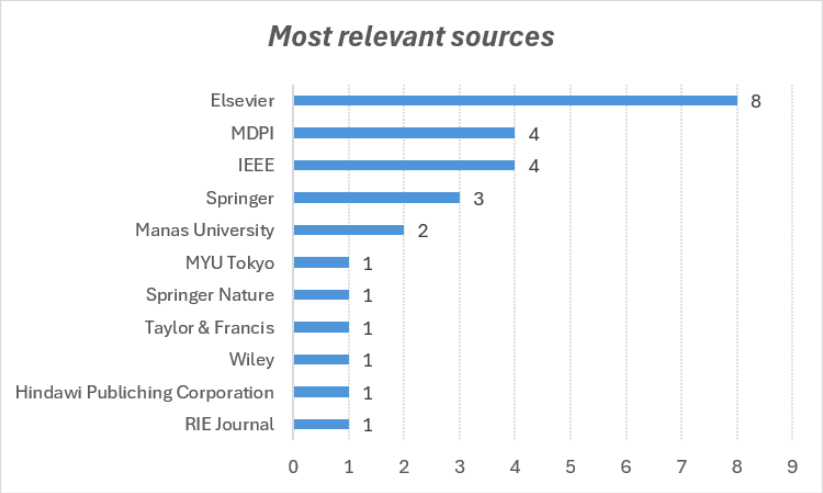


Figure 5 – Most relevant sources – Source: the author

In Figure 6, we can see that Switzerland (3), India (3), Turkey (3), and the United States (3) lead in the number of articles. Although research on this topic is concentrated in the Northern Hemisphere, there is a notable distribution across various countries, which indicates the relevance and timeliness of the topic.

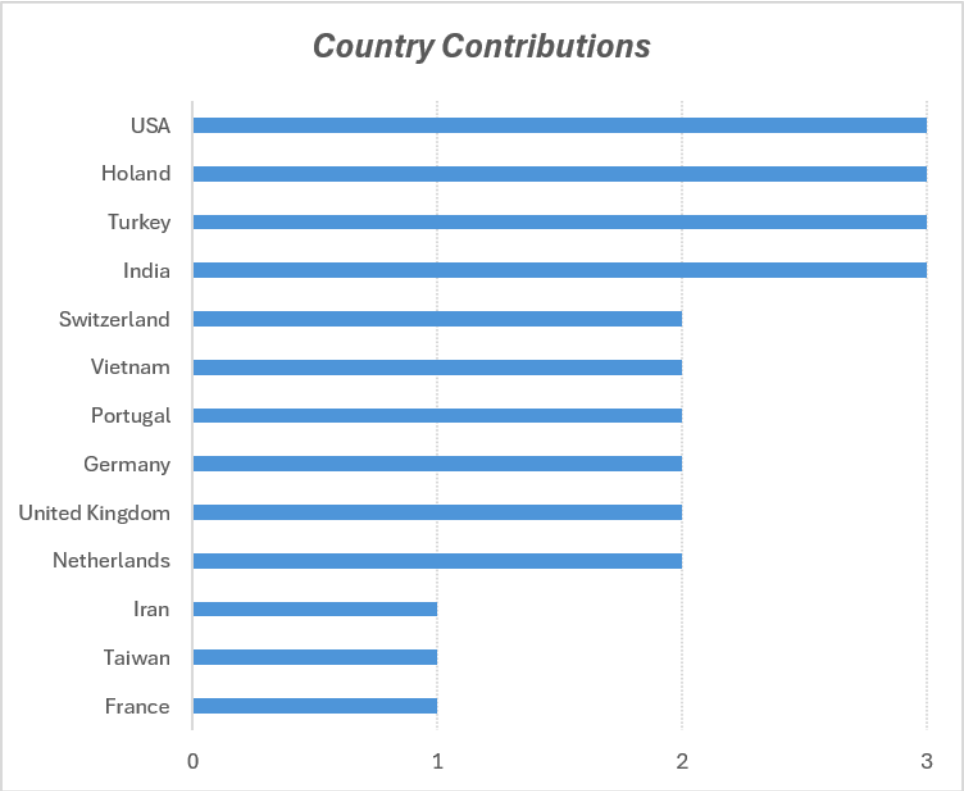


Figure 6 – Country contributions – Source: the author

Regarding the research methodology, all articles were read and considered during the development phase in an effort to clarify the scope of the application and its relevant challenges.

4. Development and Results

This section will present the results of the literature review and the development of each of the applications identified.

4.1 – Development: IoT Applications for Production Planning and Control

The following table summarizes the applications, methods, and technologies used in production planning and control, listing the main results obtained and the respective authors of the studies.

IoT Applications in PCP

Area	Authors (grouped by similar application)	Main Approach / Contribution
Dynamic Planning and Scheduling	Turker et al. (2019, 2026); Marinho et al. (1999)	DSS with IoT and real-time data for dynamic replanning; dispatching and scheduling heuristics
	Rossit et al. (2019); Na et al. (2018)	Data-Driven Planning and Real-Time Communication for Smart Manufacturing
	Coito et al. (2022); Cunha et al. (2019); Khan et al. (2025)	Dynamic Scheduling Using RFID, IoT, Fog/Cloud Computing, and Real-Time Multi-Criteria Reprogramming
Automated Industrial Planning	Quoc et al. (2025); Quoc et al. (2020)	Automatic planning based on Real-RCPSP, PSO, and evolutionary algorithms for resource allocation
APS and Rsource Allocation	Guo (2018)	APS integrated with IoT/RFID and an auction algorithm for automatic task allocation and improved planning efficiency
Autonomous Production Control	Bartsch & Winkler (2023)	Smart orders and smart contracts for self-monitoring and real-time decision-making
Cyber-Physical Integration and Smart Manufacturing	Barenji et al. (2020)	Integration of IoT, blockchain, and cyber-physical systems for distributed manufacturing execution and control
Logistics and Supply Chain	Bhargava et al. (2022)	Vehicle tracking, route planning, predictive maintenance, and logistics support using IoT and AI
Predictive Maintenance	Sekar et al. (2025); Compare et al. (2019)	Using IoT Sensors and Machine Learning for Fault Prediction and Maintenance Planning
Smart Agriculture	Jamshidi et al. (2025); Khanna & Kaur (2019)	Agricultural monitoring, pest forecasting, irrigation, and IoT-based operational planning
Digital Twin and Optimization	Amirkhanova et al. (2026)	Integration of Digital Twin, IIoT, and analytics to reduce planning time and enable rapid rescheduling
Production Planning and Control	Ersoz, O., (2019); Elhüseyni, M., (2012); Marinho, R. et al., (1999); Holthaus, O. & RAJENDRAN, C. (1999)	Definitions of Basic Concepts in Production Planning and Control
Internet of Things (IoT)	Dutta et al, (2020); Bhola et al, (2020); Rata et al,(2021); Khan, S. et al, (2025)	Definitions explaining which devices make up the Internet of Things and their applications

Table 2 – IoT Applications Aimed at Improving PCP

A decision support system is a computerized information system used to support decision-making within an organization. [2] propose a DSS (Decision Support System) that automatically collects data from the production line, analyzes the data, and intervene in order processing if necessary. Monitoring is continuous, seeking opportunities to improve production line performance and to develop better order processing and implementation strategies.

[2] propose a decision support system designed to improve the performance of rules triggered in dynamic planning using real-time data, thereby increasing plant efficiency. When the number of production orders in the queue reaches a critical value, the decision support system adjusts the scheduling of orders currently in process at the preceding workstations. Scheduling was performed using the following heuristics: earliest/latest finish, minimum/maximum buffer, minimum free intervals, and minimum delay [16]. The rules selected based on shop floor conditions are grouped into three classes: task-based rules (delivery date, processing time, deadlines), shop floor-based rules (machines planning their own resources), and hybrid rules. The simulation models must adhere to the initial assumptions. In this case, machine failures and quality issues were not considered. The time required for movement between workstations was also ignored.

[18] proposes a data-driven planning method for smart manufacturing, focusing on real-time data analysis using an IoT system to optimize production planning and improve operational efficiency. [19] developed a linked planning method for real-time data processing, also using IoT systems, in smart manufacturing systems, demonstrating the integration of real-time communication technologies in manufacturing environments.

Implementing IoT systems in industrial production allows for the collection of data directly from production lines and factories [20]. In his research, he collected information via an IoT application on an industrial sewing line directly from the sewing machines, where automatic production planning is achieved by applying a method known as Real-RCPSP (Real Resource Constrained Project Scheduling Problem), simplified through the use of the genetic algorithm (GA) and optimized particle swarm optimization (PSO), which calculate the coordination of the workflow and assigned stages within an industrial sewing line by converting the input data from contracts in accordance with the problem's constraints.

[5] presents the application of IoT for collecting key parameters for logistics planning, such as optimized route identification, real-time monitoring of logistics vehicle parameters (e.g.,

fuel levels, wheel axle vibration, and temperature), efficient maintenance planning, and predictive maintenance of logistics vehicles to ensure efficient operations.

Diverse types of sensors can be used to collect data from vehicles used in logistics, such as RPM, engine temperature, air pressure, and wheel axle vibration, and to detect any vehicle abnormalities. The IoT device will collect data from various sensors installed on the logistics transport vehicle and send it to the cloud for analysis. With the help of AI and deep learning, it will guide operators in taking the necessary precautions. This will result in time savings and the prevention of potential failures and catastrophic damage to industrial equipment [5].

Optimized route planning enables a significant reduction in operating costs and can be considered a sustainable initiative, as it reduces carbon emissions. The integration of AI and deep learning enables intelligent planning of maintenance processes that can be predicted in advance, making asset downtime more targeted and effective [5].

[21] presents a model—Information Technology–Operational Technology—applied to dynamic planning and operational replanning in a pharmaceutical setting. To achieve better integration between smart sensors and data analysis, the study presents alternatives between the use of a “fog” computing approach and a “cloud” CPU-based approach. The study presents various applications of RFID technology as a suitable alternative for real-time tracking of the production line. It is possible to identify the quantity of products and the production time for each product family at each workstation.

[22] proposes the modeling of a quality control laboratory based on a mathematical formulation of a workshop with dual-resource constraints. The main result of this implementation was the real-time integration of information between the IIoT and the company for dynamic scheduling, along with online events that affect operations and rescheduling triggers. The integration combines data from smart sensors and business information using fog computing to calculate whether rescheduling is necessary.

[3] propose the use of smart orders via smart contracts for autonomous routes based on a code of programmed information, enabling self-control throughout the production system. Through IoT-based monitoring during production, orders are tracked for scheduled progress and capacity utilization. Order, machine, and personnel data are continuously collected as part of production data acquisition for monitoring purposes. This data is used to constantly compare actual data with planned data, allowing for immediate corrective action in the event of deviations. Analyzing the effects of measures prior to implementation also allows for an assessment of their potential impact.

Using radio-frequency identification (RFID) and IoT technology, [13] tracked information on production equipment and products at various points in the process, with real-time updates. The information was used in the APS system to improve production efficiency and planning.

Using a task allocation algorithm based on a sequential single-item auction, the task is assigned to the production equipment resource. This study uses an IoT module and RFID technology to collect information about production equipment, reducing the time spent on manually collecting this data [13]. The collected information is then entered into an automated production planning system (APS). Production planning efficiency is nearly 10 times higher when using the APS system compared to manual planning. With the use of IoT and RFID technology, the entire production information and planning process can become significantly more efficient.

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using the APS system compared to manual planning. With the use of IoT and RFID technology, the entire production information and planning process can become significantly more efficient.

An intelligent monitoring and management system based on the Internet of Things (IoT) was developed and implemented for apple orchards by [11], with the goal of monitoring environmental conditions in the orchard, predicting the most significant diseases and pests, and managing irrigation and fertilization. The results showed that the smart system is capable of informing the user about the best times for spraying and providing practical recommendations for controlling biological threats. Better planning of spraying routines reduced losses caused by diseases and pests, thereby improving productivity. Consequently, effective pest control reduced the use of fungicides and pesticides (by more than 33% and up to 50%, respectively), improving the quality of the apples in terms of chemical residues.

In industry, manual or time-based inspections are two examples of traditional maintenance practices; they are not equipped to anticipate complex system interactions in real time, which leads to high costs and inefficiency [23]. In this article [23], the authors present a conceptual model in which sensors are attached to equipment over an extended period, and through various machine learning techniques, the model is progressively refined and trained, thereby improving the performance of maintenance planning.

[1] presents a multi-criteria adaptive scheduling method that performs accurate and efficient planning or rescheduling of production stages in real time, taking into account shop floor information (operators, machines, etc.) and condition-based service requirements. In this type of application, the number of IoT devices is equivalent to the number of products being produced simultaneously; request agents and source agents interact when rescheduling the processes of the n products being produced due to a complex change in the position of a single asset.

The implementation of digital twin technology reduced daily manual planning time by 87.4%, and material management KPIs improved, enabling faster rescheduling in response to changes in demand. Planning automation was achieved through the design and implementation of low-level code that integrates the HFSP optimizer and DT (digital twin) data into daily operations. Implemented through low-level code planning applications that integrate the HFSP optimizer and DT (digital twin) data into daily operations [24].

[25] implemented an automated production planning method based on data collected from the IoT system and on data regarding apparel contracts signed with companies. Automated production planning is carried out by applying the Real-RCPSP (Resource-Constrained Project Scheduling Problem). The solution to this problem consists of a schedule for allocating the company's resources to the execution of each stage of product production in accordance with the apparel contract. The input data for this problem is derived from apparel contracts, in accordance with the problem's constraints. Experiments conducted with the PSO algorithm show that the production plan automatically generated by the Real-RCPSP problem significantly reduces production time, which helps companies improve production efficiency, increase profits, and enhance their competitive advantage.

4.2 Results and Discussion

The evidence gathered shows that the application of the Internet of Things (IoT) in production planning and control (PPC) serves as a central element in the transition from traditional systems to dynamic, intelligent, and automated models. The integration of sensors on the factory floor, combined with Decision Support Systems (DSS), enables the collection, processing, and analysis of data in real time, allowing for rapid and, in many cases, automatic interventions in production orders. This context reinforces the role of the IoT as an enabler of dynamic planning, in which tasks and operational conditions are constantly changing, requiring frequent and adaptive rescheduling.

In this scenario, it is evident that combining classical programming heuristics with real-time data significantly increases the accuracy of decisions, since the planning process now reflects the current state of production. At the same time, the literature shows that many models still rely on simplifications, such as the exclusion of failures and variability, which points to opportunities for improvement through the incorporation of artificial intelligence and machine learning. This evolution is a natural progression, given that such technologies expand the systems' capacity for predictive and adaptive analysis.

The results also highlight the importance of the IoT in advanced data-driven planning methods, including the application of algorithms such as Real-RCPSP, genetic algorithms, and particle swarm optimization. These models offer a high degree of automation, especially in complex environments such as sewing lines, where automatic data collection directly from the machines eliminates the need for manual intervention and increases the reliability of the information. Consequently, planning now takes into account real and dynamic constraints, leading to more accurate schedules, better resource allocation, and improved coordination of production flows, with significant gains in efficiency and competitiveness.

Another important aspect relates to the continuous monitoring provided by the IoT, which covers both physical variables—such as temperature, pressure, vibration, humidity, and speed—and operational indicators, such as productivity, machine efficiency, order status, and resource utilization. The integrated analysis of these variables enhances visibility into the production system, enabling the identification of deviations in real time and the immediate implementation of corrective actions. Additionally, the inclusion of logistics and maintenance parameters—such as fuel consumption, routes, and wear and tear—strengthens the integration between production planning and control (PCP), maintenance, and logistics.

In this context, the shift from reactive maintenance to predictive approaches—made possible by the use of sensors and machine learning techniques—stands out. Continuous data analysis reduces unplanned downtime and minimizes false positives, contributing to lower operating costs and increased production efficiency. Similarly, IoT-based logistics applications enable route optimization and greater sustainability, with reduced emissions and better use of resources.

The integration of IoT, computing architectures (cloud and fog), and traceability technologies, such as RFID, is also proving to be fundamental to the consolidation of smart manufacturing. This combination provides real-time visibility into orders, resources, and production performance, facilitating continuous replanning. Studies indicate significant productivity gains, especially in APS systems when compared to manual planning, as well as the emergence of concepts such as smart orders and automated contracts, which signal the evolution toward autonomous systems.

In addition, there is a shift toward highly integrated models, such as digital twins and multi-criteria adaptive systems, which use data from the IoT for simulation and continuous optimization. These systems deliver significant reductions in planning time—in some cases exceeding 80%—and substantial improvements in operational metrics. The ability to reprogram in real time increases the resilience of the production system in the face of demand fluctuations and unexpected events, solidifying the role of the IoT as the foundation of digital transformation in the PCP.

Despite the evident benefits, the implementation of the IoT still faces significant challenges. Among the main technical barriers are device storage and processing limitations, energy consumption, communication latency, and the need for adequate infrastructure for distributed computing. Furthermore, correctly defining the variables to be monitored and selecting the most appropriate devices are critical factors for the application's success, requiring alignment between strategic objectives and technological capabilities.

From an organizational perspective, issues such as implementation costs, integration with legacy systems, interoperability, and resistance to change also pose significant obstacles. The complexity associated with adopting complementary technologies, such as blockchain, and the lack of understanding regarding the benefits of the IoT can hinder its adoption in traditional industrial environments.

Thus, the results discussed confirm that, although the IoT is an essential enabler of smart manufacturing and automated planning, its implementation requires overcoming technical, economic, and cultural challenges. Nevertheless, the observed gains in efficiency, accuracy, and adaptability indicate strong potential for this technology to become a cornerstone of the future of production planning and control.

5. Conclusion

The implementation of IoT systems embedded in equipment throughout the entire production flow allows data to feed back into production planning in real time and enables control measures to be taken with a focus on performance and customer value. Interactivity and algorithm improvements combined with AI make the reallocation and course correction of production orders increasingly autonomous, making dynamic planning a reality and better aligned with the needs of Industry 5.0.

The adoption of IoT technologies in the manufacturing environment represents a significant advance in how production planning and control are conducted, especially in dynamic and highly variable scenarios. The ability to collect data in real time enables continuous monitoring of operations, reducing uncertainty and increasing the reliability of management decisions. Furthermore, communication between devices and systems—made possible by the IoT—strengthens integration across different organizational levels, from the shop floor to strategic management systems. This continuous flow of information directly contributes to improved operational efficiency and the reduction of wasted time and resources. Another relevant aspect is the feedback loop in planning, which is continuously adjusted based on real-time, up-to-date data. Thus, the rationale for this study is confirmed by demonstrating that the IoT not only supports but transforms the traditional logic of production control.

In this context, the use of IoT combined with technologies such as cloud computing and artificial intelligence underscores the importance of intelligent systems capable of responding quickly to unforeseen events. The study shows that the digitization of production processes enables greater visibility and control, raising the level of maturity of industrial operations. Connectivity between machines, operators, and systems enables decentralized and more agile decision-making—an essential characteristic of Industry 4.0 and 5.0. Furthermore, continuous monitoring contributes to more advanced practices, such as predictive maintenance and automatic resource optimization, reducing failures and improving the overall performance of the production system. The rationale presented is further supported by highlighting the positive impact on creating value for customers and increasing companies' margins. Thus, IoT integration is established as a key element for the evolution of production planning and control in modern industrial environments.

As a proposal for future studies, we suggest further exploring the integration between IoT and artificial intelligence, especially in the development of predictive models applied to production planning and control. Research could explore the use of machine learning algorithms to anticipate failures, optimize production sequencing, and improve real-time resource allocation. Another promising area involves the application of digital twins combined with IoT and AI, enabling more realistic simulations and more informed decisions prior to implementation in the physical environment. Analyzing the reliability of the collected data and its integration with secure platforms, such as blockchain, is also a relevant topic. Finally, future research may focus on the economic feasibility of these solutions and the challenges of interoperability with

legacy systems, thereby expanding the practical applicability of these technologies across different industrial sectors.

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