An overview of the current state of development of the production planning and control systems within the industrial sector

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Abstract. This paper analyzes the current state and future development of production planning and control systems in the context of Smart Factories and Industry 4.0. The study highlights the increasing need for flexibility, transparency and rapid decision-making in modern manufacturing environments characterized by high product variety, short delivery times and volatile demand. A comparative assessment of the main production planning and control approaches, including MRP/MRP II, ERP, MES, Kanban and intelligent production planning and control systems, is presented. The analysis shows that traditional planning methods based on fixed lead times and rigid forecasts are no longer sufficient in highly dynamic production environments. Particular attention is given to the role of MES systems as a real-time interface between planning and execution, enabling improved monitoring, resource utilization and quality control in discrete manufacturing. Furthermore, the paper discusses the growing importance of intelligent and adaptive planning methods supported by multi-objective optimization, heuristic algorithms, Internet of Things technologies and Digital Twin concepts. The results emphasize that effective production management requires the integration of strategic, tactical and operational planning levels and continuous data exchange between information systems and shop-floor equipment. Finally, the Romanian industrial context is examined, indicating favorable conditions for the adoption of Smart Factory solutions, while also underlining the challenges related to system integration, data standardization and workforce development.

1. Introduction

A “key feature of Industry 4.0” [1], the Smart Factory “is defined as a factory that, in a context-aware manner, supports humans and machines in performing their tasks. This is achieved through systems that operate in the background, the so-called ‘calm systems,’ meaning that the system can take into account contextual information such as the position and condition of an object. These systems perform their tasks based on information originating from both the physical and virtual worlds. Information from the physical world includes, for example, the position or condition of a tool, in contrast to information from the virtual world, such as electronic documents, drawings, and simulation models. In this context, calm systems refer to the hardware of a smart factory. The main difference between calm systems and other types of systems lies in their ability to communicate and interact with their environment" (Lucke et al., 2008) [6].

The Smart Factory (Intelligent Factory) represents a step forward from a traditional automation system to a fully connected and flexible system, one that can use a continuous flow of data from connected production operations and systems to learn and adapt to new requirements. Product design and manufacturing processes have become highly competitive therefore, a new level of integration is required, which will create flexibility, automatically propagate changes, increase reusability, and minimize errors and waste-related costs.

The benefits of the Smart Factory within Industry 4.0 include:

- *Time* (Each employee becomes more efficient when working within an optimized process. Engineers typically spend 31% of their working hours searching for information—time that could instead be used for value-adding activities);
- **Cost** (Software systems present specific data in the correct context and format required for informed decision-making. Misinformation and erroneous decisions based on it cost companies approximately 25% of their revenues);
- Integration (Digital manufacturing involves the simultaneous development of the product and the production process. Companies can reduce production downtime by up to 80% when using digital validation);
- Flexibility (The creation of flexible systems that are ready for change and prepared for new opportunities. Approximately 36% of companies are ready to optimize their processes based on data analysis [2].

2. Smart Factories

The key factors in Smart Factory design (Figure 1) are:

- Connectivity – processes, machines, and people are connected to improve efficiency;
- Optimization – high levels of automation to increase productivity;
- Agility – configurable factory layouts and real-time implementation of product changes;
- Transparency – visibility across all operations to enable real-time decision-making;
- Proactivity – automatic replenishment, fault detection, and safety monitoring [2].

Figure 1. Smart Factory (CISCO – IoT solution) [4].

2.1. Challenges of a Smart Factory

A smart factory employs the latest technologies in fields such as artificial intelligence, robotics, analytical tools, and the Internet of Things (IoT), a term referring to the billions of devices worldwide that are connected to the Internet and continuously engaged in data collection and exchange processes. The objective of this type of factory is to operate autonomously, with minimal human intervention. A Smart Factory is more complex than mere software; its defining characteristics are visibility, connectivity, and autonomy. Although many factories already rely on partial automation, smart factories take this concept much further, being able - at least theoretically - to operate independently, without human intervention. By using modern technology, intelligent factory systems learn and adapt in real time, allowing production units to become more flexible [2].

The processes that enable a smart factory to operate include:

- The extensive use of sensors and specialized devices that connect machines and make factory processes visible, while simultaneously building what is known as the Industrial Internet of Things (IIoT);
- *Artificial intelligence*-based applications and the ability of machines to learn and perform routine operations, which allow factory personnel to focus on more important tasks.

In the near future, these smart factories are expected to be populated by robots performing routine work, collaborating with humans (cobots – collaborative robots).

Smart factories build bridges that create a more efficient management chain. They are also based on production systems that use the Digital Twin, a virtual representation of a product that can be used in design, simulation, optimization, and service activities - a core IoT concept that digitally connects the product to all stages of its life cycle. In addition, production machines can be integrated into the execution system network to receive orders, report progress, access work instructions, and interact with quality management systems. This makes it easier for workers to access important information, such as inventory status. In short, a fully connected Smart Factory means that all equipment is interconnected, and all departments within the factory are connected both with each other and with external suppliers and customers, which improves and simplifies relationships. As a result, activities can be monitored, enabling the factory to increase its speed and efficiency.

The smart factory, which is being rapidly realized particularly through equipment automation, operates autonomously and can identify, diagnose, and repair faults without stopping the entire production line. Industry 4.0 combines computing capabilities with industrialization in order to develop more functional production lines. Although the technologies required to create a smart factory already exist and some companies are already enjoying the benefits, a major challenge remains: data integration. All segments of a smart factory should be perfectly interconnected, which implies working with enormous volumes of information. The true strength of such a factory lies in its ability to evolve according to organizational needs, whether these relate to customer demand or the development of new products.

Specifically, the problems currently faced by factories in the automotive industry are related to the use of *Overall Equipment Effectiveness* (OEE) tracking systems, which no longer meet the requirements of smart manufacturing and exhibit a number of shortcomings [2].

With regard to pre-production, these shortcomings include:

- Data for OEE production monitoring systems are entered manually;
- An overview of scrap volumes and a general presentation of clusters are not available at the end of the shift;
- There is no transparency regarding real-time machine availability;
- Fulfilment of the production plan is not available in real time [2].
- Regarding to assembly, there are also several issues that current production monitoring systems (e.g., OEE) cannot manage efficiently:
- Performance can only be calculated for the previous day;
- Waste is not identified by cell clusters and must be entered manually at the end of the shift;

- Corrective actions regarding production plan fulfilment cannot be carried out in real time, making it very difficult to achieve or increase labor productivity;
- All KPI information is valid only for the previous day and not for the current one.

Addressing these shortcomings requires the development of a *Manufacturing Execution System* (MES) capable of efficiently managing both the pre-production and assembly areas, based on the individual customization and parameterization of the various variables involved in the production process/system.

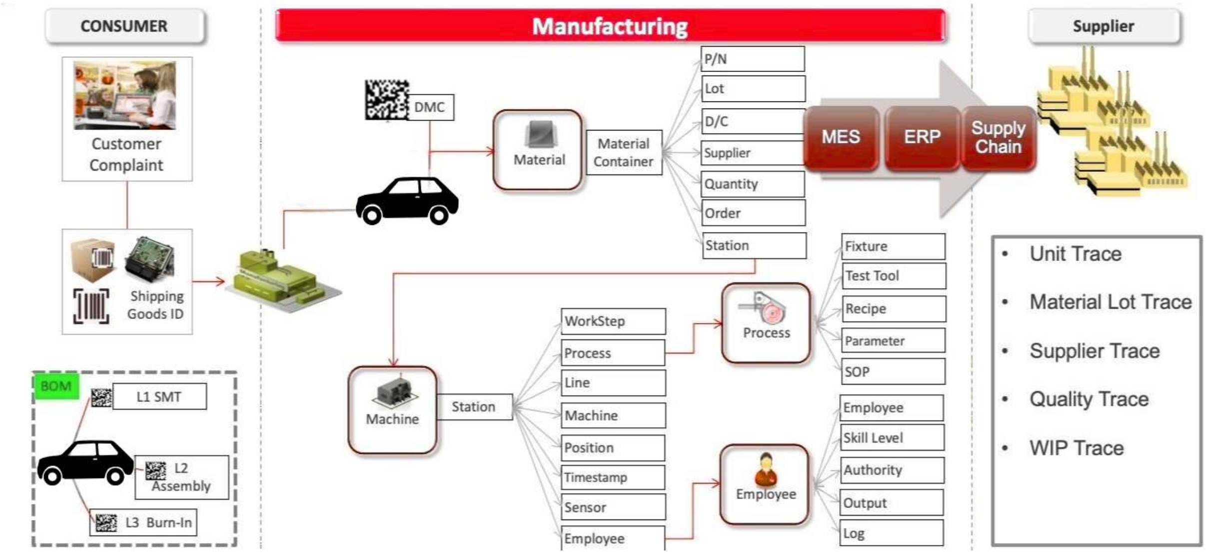

Figure 2. Manufacturing Execution System-MES [2].

The advantages of using a Manufacturing Execution System (MES) for production monitoring (Figure 2) include:

- Cost-optimized planning based on real-time data;
- Transparency of complex production processes (Figure 3);
- Compliance with OEM conformity standards;
- Quality assurance;
- Increased efficiency through continuous process optimization;
- A predictive maintenance solution, designed to reduce waste and avoid downtime [2], [3].

Figure 3. Production systems monitoring interface [5].

2.2. Systems Specific to Smart Factories

Discrete, process, and even hybrid manufacturing require a specific approach to organizing the manufacturing process. This involves performing individual operations in either a continuous or discontinuous manner. This production organization technique is frequently used in industries such as mechanical engineering, computer manufacturing, electronics, and other related or specialized fields where there is a need to control and account for individual components and the processes used in manufacturing. This enables the creation of products with specified characteristics [4]. Due to the requirement for precise control and batch-based accounting, the planning process may differ from traditional continuous manufacturing and requires monitoring at each stage. For a further analysis of production planning, it is essential to examine in more detail the characteristics of this approach as a whole. One of the most important factors to consider is the ability to create small-series or even unique products [5].

In addition, it is important to note that customization is feasible only for specific components or aspects of a finished product, and this does not significantly extend production time, thereby allowing mass production. This approach enables companies to adapt their offerings to customer needs and remain competitive by extending product specifications to meet individual customer requirements. However, for a comprehensive analysis, continuous (process) production must also be considered. It is essential to understand the characteristics of this approach, to analyze and identify the key differences compared to discrete production. This will provide a new perspective not only on the characteristics and complexities of discrete manufacturing, but also on highlighting the main benefits of continuous production more prominently.

Continuous production involves organizing the production process in a manner that avoids interruptions. As a result, this method often operates without human intervention, using a maximum level of automation. Moreover, processes within continuous production are standardized, with all equipment performing the same function throughout the production cycle. This method minimizes the time and resources spent on equipment reconfiguration, ensuring consistent product quality. Continuous production also requires fewer complex quality management systems, as control is implemented at the level of the entire process. For example, in the chemical industry, quality assurance can be integrated into the production process, and deviations can be identified during sampling. Therefore, it can be concluded that, in this scenario, less emphasis is placed on individual products, as the entire production flow is viewed as a cohesive unit.

When comparing discrete and continuous production methods, several factors must be considered in order to determine which method is most appropriate. These factors include product type, quality standards, production volume, and flexibility in adapting to market changes and product variations. For example, in the case of discrete production, the manufacturing of electrical appliances can be considered. This type of production usually requires a high degree of customization and significant changes in the production process. This can lead to improved quality control while maintaining the flexibility needed to adapt to changes in production plans [6].

After identifying and analyzing the circumstances in which the use of individualized production techniques is appropriate, it is essential to consider whether such methods may not be applicable in certain fields under specific conditions.

3. The Production Planning

3.1. The Production planning levels

Discrete production planning is a complex, multi-level process that requires careful analysis of the various factors affecting production efficiency and flexibility.

An important aspect of this process is adaptability, which demonstrates the quality and effectiveness of planning depending on how quickly the overall plan can be adjusted to changing circumstances. It should be noted that adaptability must be considered not only in general, but also at different planning levels: strategic, tactical, and operational. Strategic planning involves decisions regarding long-term objectives and the development of production capacity. Tactical planning involves medium-term resource allocation, while operational planning focuses on daily operations and the management of specific tasks [7].

In this context, these levels can be conceptualized in terms of a hierarchical structure. The highest level is the strategic level, followed by tactical levels and then operational levels. This illustrates the interdependence among these levels and their mutual dependencies (see Figure 4). Thus, a change at the strategic level may affect planning activities at both the tactical and operational levels.

Figure 4. The Production planning levels [1],[7].

The strategic level of planning is of the greatest importance and influences all other planning levels. It focuses on long-term objectives and goals for the overall growth and development of the organization, with the primary aim of establishing a shared vision and determining key priorities that can help the company achieve a competitive advantage. To this end, at this level, companies engage in preliminary market research to collect critical strategic information [8]. This includes:

- Analyzing the market value represented by the company and determining how it can best position itself toward the target audience;
- Market analysis;
- Identifying the target audience;
- Assessing the competitive landscape.

Decisions are also made regarding growth direction, the development of new products, and the markets the company intends to enter. Furthermore, it is essential to note that, at this stage, decisions are taken concerning the expansion of production capacity, modernization of equipment, or implementation of new technologies. A key objective is also the evaluation of the investments required to achieve the established goals. This includes determining the financial, material, and human resources necessary for implementing the strategy. In addition, companies at this stage analyze external and internal factors that may affect their business in order to identify potential risks and growth opportunities and to develop adaptive strategies accordingly.

The tactical planning level is situated at the intermediate level and consists of planning over medium-term horizons, ranging from several months to several years. This level of planning operates with tasks and objectives that translate strategic-level plans into more detailed plans. As an example, a tactical planning task may involve the development of a detailed production plan that determines which goods will be produced, in what volumes, and within what time frame.

Another important characteristic of tactical planning is the consideration of demand seasonality and market fluctuations, which allows the company to respond flexibly to external changes. The tactical level also covers the management of inventories of raw materials, components, and finished products, enabling efficient inventory planning and contributing to cost reduction. Moreover, this aspect of tactical planning helps prevent material shortages, which in turn supports uninterrupted production. It should be noted that an important element of tactical planning is also resource allocation, including labor, equipment, and materials, which enables optimization of the production process.

The operational planning level refers to the lowest level of the planning hierarchy and focuses on short-term objectives and tasks that are typically accomplished within a day or a week. This form of planning is essential for managing daily operations and achieving specific minimum production targets. Operational planning involves assigning tasks among team members, creating and managing work schedules, and ensuring that production standards are met and necessary resources are available. This approach helps optimize the manufacturing process, reduce costs, and promptly address emerging issues. In addition, quality control measures are implemented at this level to ensure that products comply with established standards. This is essential for maintaining the company's reputation and meeting customer expectations.

It is also important to consider a discrete approach to production planning, such as the PDCA cycle (Plan–Do–Check–Act) (see Figure 5). This concept has its own characteristics and benefits for implementing adaptive planning. PDCA is a continuous process improvement tool that can be adapted to optimize various aspects of production [9].

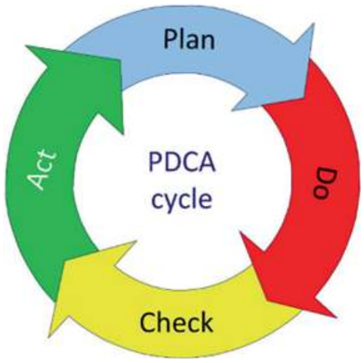

Figure 5. P.D.C.A. Cycle [9].

The *PDCA* (Plan–Do–Check–Act) cycle is crucial for enterprises not only for effective planning, but also for improving product quality. Each cycle involves quality control and analysis to ensure process quality, as well as addressing the need to adjust the entire technological process, which may be caused by changes in market requirements or resource availability [9].

The application of the PDCA cycle in production begins with the *Planning* **(**Plan**)** stage. At this stage, goals, objectives, and resources are identified and defined in order to plan and achieve future results. The planning process starts with an analysis of production processes and technologies, detailed planning of production activities, calculation of required resources, estimation of task completion times, and establishment of production priorities. It should be noted that minor adjustments may be made at this stage based on feedback from the Execution (Do) stage, which will be discussed later. However, it is important to understand that this approach may not always be fully accurate, as the Planning stage operates only with the data available at that moment.

Next follows the *Execution* **(**Do**)** stage, which involves taking the plans developed in the previous phase and putting them into practice. At this stage, specific production activities outlined during the planning phase are carried out. In discrete manufacturing, this may include activities such as launching a new production line, adjusting equipment, or implementing new technologies. A critical aspect of this phase is ensuring that all activities are performed in accordance with established quality standards and criteria. These criteria are verified through rigorous production monitoring techniques in order to detect any deviations from expected performance indicators at an early stage. Any deviations are addressed promptly to ensure that the production process remains on track [10].

The third phase of the process is known as *Checking* **(**Check**)**. This stage involves reviewing the results of plan implementation, comparing these results with expected objectives, and implementing quality control measures. In discrete manufacturing, this phase covers product quality assurance, analysis of performance indicators, and identification of areas for improvement. For example, if during the implementation phase it is observed that certain activities take longer than anticipated or product quality does not meet standards, this triggers a review of the reasons behind these deviations. This step is crucial for identifying weaknesses in the organization's production process and determining the changes and improvements required to enhance efficiency and quality.

The final stage of the process is *Action* (Act). During this stage, specific actions are undertaken based on the results of the previous checking phase. These actions may include adjusting production schedules, modifying manufacturing processes, implementing new quality control measures, and reconfiguring assembly lines. In discrete manufacturing, companies may also choose to adjust equipment, revise employee schedules, or modify material handling procedures. The main purpose of this stage is to take specific actions based on the information collected in previous phases. These actions aim to improve the manufacturing process, reduce costs, minimize waste, and increase customer satisfaction [11].

As a main conclusion regarding the application of the PDCA cycle in discrete production planning, it can be stated that its systematic approach to each process results in continuous process improvement. This approach enables adaptation to changes in the external environment, effectively addressing issues related to fluctuating demand, limited resources, and the need for quality improvement. Through regular implementation of the PDCA cycle, enterprises can enhance production flexibility, minimize the risks of errors and downtime, and optimize the use of equipment and resources. These advantages make the PDCA cycle an indispensable tool in production, as success depends on a company's ability to continuously improve its processes and rapidly adapt to changes in external circumstances [12].

Nevertheless, considering all the above aspects, it is essential to also address the issue of adaptive planning in the context of certain limitations. Among the main limitations are the lack of available resources, the time required to fulfil orders, and uncertainty regarding demand. These factors can pose significant challenges in terms of flexibility and adaptability of production processes. For example, fluctuations in product demand may require rapid reconfiguration of manufacturing lines. Such actions require efficient management and strategic planning, which can be difficult due to the unpredictable nature of demand. Although the capability to implement such measures has been discussed in a previous section, the additional challenge of unpredictable demand makes it difficult to generate accurate forecasts. As a result, this may negatively affect the planning process and lead to suboptimal allocation of resources. It is also important to analyze separately and in greater detail the issue of demand variability, as it significantly affects changes in order fulfilment time. Under conditions of fluctuating demand, enterprises may find themselves in a situation where customer orders cannot be fulfilled in a timely manner, leading to customer dissatisfaction and potentially to a decline in the company's competitive position. To minimize these risks, it is essential to consider flexibility and adaptability in advance. Implementing procedures that allow for easy change is crucial, ensuring that such change is not only feasible but also non-critical. This will enable enterprises to respond more promptly to market changes and adjust production plans in line with actual customer requirements [13].

Another significant consideration is the limited availability of resources and the need to optimize equipment utilization. Even minor changes in equipment loading can lead to substantial financial losses and a reduction in total output. In addition, changes in production conditions may result in downtime and losses. For example, if there is an unexpected need for equipment replacement or delays in material supply, this may lead to production line stoppages. Such situations negatively affect overall performance indicators and may hinder the fulfilment of production plans. To minimize these losses, it is important to implement flexible planning systems that take potential changes into account and allow flexibility in managing the production process [14].

Therefore, the key conclusion regarding the difficulty of adaptive production planning is that it requires balancing various factors, such as multidimensional planning, uncertain demand, constrained resources, and potential downtime. To effectively address these challenges, it is essential to implement modern methods and techniques that enhance the flexibility and agility of production processes. These measures will enable enterprises to compete successfully in a rapidly evolving market environment.

3.2. Discrete Production Planning Systems

3.2.1.MES class systems

The adoption of a Manufacturing Execution System (MES) for discrete production planning has become a fundamental component in improving productivity and increasing the efficiency of manufacturing processes. An MES is a software solution that acts as a link between the planning and production tracking phases, enabling companies to manage their operations more effectively. In today's dynamic and competitive business environment, adaptability, accuracy, and process control are paramount. Implementing an MES significantly enhances management's ability to plan and, especially, to monitor production activities, resulting in optimized resource allocation and reduced waste. The system's real-time data collection and analysis capabilities allow managers to make rapid and well-informed decisions, enabling production adjustments as needed in order to maximize efficiency.

At the same time, the primary objective of an MES is to integrate and coordinate all stages of the production cycle, from planning to execution. This makes it a crucial tool for modern enterprises (Smart Factories). The use of an MES enables the development of production plans during the planning phase, supports resource allocation, and ensures the timely completion of orders. This is particularly important for discrete manufacturing, where products are frequently produced as individual units or in small batches. Therefore, meticulous control over each stage of the manufacturing procedure is essential. With the support of an MES, it becomes feasible to create a comprehensive production plan for a manufacturing unit, taking into account not only current equipment load, but also resource availability and logistical support [15]. Moreover, MES provides real-time monitoring of production operations, enabling the tracking of key manufacturing process indicators such as equipment performance, actual operating times, defect levels, and deviations from planned objectives. This type of analysis is essential in discrete manufacturing environments, where each production cycle may have unique characteristics. By ensuring this level of supervision, problems can be identified and resolved before they negatively affect product quality or order delivery dates. This leads to a reduction in errors, downtime, and inefficient equipment usage, ultimately accelerating the production cycle and increasing overall efficiency.

Another significant aspect of using MES systems for production planning concerns quality management. These systems often incorporate functions designed to monitor product quality indicators at each stage of the manufacturing process, which is a critical factor in production environments where products pass through multiple processing stages. By monitoring quality at each stage, defects can be prevented and compliance with standards can be ensured. The MES automatically collects data on manufacturing operations, enabling real-time tracking of product quality and rapid response to any issues.

MES also plays an essential role in optimizing resource management, which is a crucial aspect of production planning in general. In this type of planning, there is often the challenge of limited resources, such as equipment, materials, and labor. MES enables more efficient resource management by providing accurate information about the current status of the production process and equipment utilization. This information allows rapid adjustments to production plans and helps avoid downtime or overutilization of individual production facilities. In addition, optimizing equipment utilization is particularly important, as adjusting production lines for different product types can be time-consuming and labor-intensive, as is often the case in mechanical engineering. Furthermore, MES contributes to the reduction of waste and production defects. The system collects and analyzes data throughout the manufacturing process, enabling rapid identification and correction of deviations from standards. For example, if there is a recurring problem with defects at a particular stage of production, MES can immediately alert the operator or supervisor, allowing corrective actions to be implemented. This, in turn, reduces the number of defective products manufactured and minimizes losses associated with processing or disposing of defective items [16].

It is also worth noting that MES systems contribute to improved communication between different departments within an organization. This is achieved through the storage and management of data from the entire production process within a unified information system (IoT). Consequently, all departments involved in planning, logistics, and quality control have access to a wide range of data and can quickly obtain all relevant information. This enables informed decision-making, increases transparency in the manufacturing process, and minimizes the risk of errors. Moreover, it accelerates the decision-making process, resulting in more efficient operations.

In conclusion, the implementation of MES in specific production processes allows improved control over various aspects of production, from planning to execution and quality assurance. This leads to cost reduction, increased productivity, and improved product quality. Furthermore, the system provides enhanced flexibility and adaptability, which are crucial in a rapidly evolving market [17].

MES has become an essential tool for companies operating in the manufacturing sector, as it offers competitive advantages and supports operational success. However, it is essential to acknowledge that frequent plan adjustments may be infeasible in the absence of real-time adaptive planning techniques. Despite this challenge, MES remains a high-quality software solution for supporting productive activity.

3.2.2. ERP class systems

The implementation of an *Enterprise Resource Planning* (ERP) system is essential for enhancing the efficiency, consistency, and flexibility of production operations. This system integrates various business functions—such as production planning, resource management, procurement, logistics, finance, and sales—into a centralized information system, thereby facilitating the management of complex processes and coordination across departments. For manufacturing companies, this integrated approach is particularly beneficial, as it enables accurate order scheduling and optimized resource allocation. By consolidating all relevant information and processes into a unified system, companies can ensure precise order fulfilment while simultaneously reducing costs [18].

To initiate a study on the implementation of an ERP system for discrete production scheduling, it is essential to examine the feasibility of integrating all business processes. In the context of discrete manufacturing, where products are assembled from individual parts, seamless coordination among different production stages is crucial. The ERP system acts as a critical tool for automating and harmonizing data across various departments within an organization, significantly facilitating planning and resource allocation processes. For example, an ERP system can be used to manage inventory levels and ensure the timely delivery of materials and components, minimizing the risk of delays caused by resource shortages and ensuring orders are completed on time. In addition, ERP enables companies to monitor the current status of orders, anticipate future material requirements, and adjust production plans accordingly.

Furthermore, it is crucial to consider the capabilities of ERP systems, particularly with regard to resource management, which is a significant feature of these systems. In manufacturing, there is often a high level of product variety and a need for rapid response to changing customer requirements. An ERP system can help companies more accurately forecast their material, financial, and human resource needs. For instance, it can provide information on equipment utilization and work schedules, as well as determine whether additional personnel are required to fulfil specific orders. This is essential to ensure timely order completion without excessive inventory accumulation or overloading production facilities [18].

Considering the timeframes and planning horizons discussed in the previous section, it is clear that the ERP system provides opportunities for both long-term and short-term planning at the strategic and operational levels. At the strategic level, ERP facilitates the development of future plans that take into account business requirements for production facilities, expansion, and modernization strategies. On the other hand, at the operational level, the system supports daily and weekly operational planning, ensuring the timely completion of ongoing production tasks. This is made possible by the system’s ability to systematically collect data on order fulfilment and production progress in real time, allowing the company to respond more adaptively to demand fluctuations, schedule deviations, and changes in production conditions.

Finally, a significant advantage of ERP systems is their ability to adapt to specific business requirements. Modern ERP solutions are modular and configurable, allowing them to be customized according to the needs of any organization, whether it produces complex technical products or large-scale standard items. This adaptability makes ERP a versatile tool that can benefit both large corporations and smaller companies involved in discrete manufacturing [19]. The ERP system is a powerful instrument for designing and managing manufacturing processes, as it integrates all business operations and improves resource management. This leads to more efficient planning, improved product quality, and lower costs. By implementing an ERP system, companies can better respond to market changes, enhance internal processes, and ensure high-quality products, thereby increasing their competitiveness in the global market.

However, it is also worth considering the ERP system from a technical perspective. Such systems employ NP-complete algorithms as mathematical planning techniques, which can lead to an exponential increase in planning complexity as more variables are incorporated. At the same time, enterprises must be more adaptable in their planning in order to respond to changing circumstances. In the next chapter, an alternative solution will be presented.

3.2.3. The MRP system

The Material Requirements Planning (MRP) was introduced by Orlicky [23] and has served as the backbone of manufacturing software systems for half a century. MRP is the computational engine that, based on planned lead times for procurement and production, specifies what to produce or order, how much, and when. In an effort to improve the effectiveness and reliability of MRP in meeting customer order due dates, MRP systems evolved into Manufacturing Resource Planning (MRP II). The latter essentially establishes manufacturing schedules not only on the basis of demand forecasts, but also according to production capacity requirements and availability [21].

With the objective of achieving better planning and control of company activities, the MRP II approach further evolved - particularly during the 1990's - into what is known as Enterprise Resource Planning (ERP). In addition to production resources, ERP includes the planning and control of all resources required for company operations, including financial resources [22].

One of the main requirements of MRP-based systems is the use of production lead times for each production phase as a means of determining the delivery time of each component in the bill of materials for every product.

In MRP, these lead times are typically established regardless of shop-floor workload. Moreover, given the inherent characteristic of MRP to make component demand dependent on final product demand, achieving delivery lead times requires that all material requirements be based on forecasts.

However, because forecast reliability is low due to today's volatile and variable-demand markets, the MRP approach is likely to result in overproduction in certain periods and shortages in others. This situation requires continuous adjustments to supply and MRP production schedules as actual demand becomes known.

The continuous adjustment of demand for finished products leads to continuous adjustments in demand for the various product components and required raw materials, creating a phenomenon known as "MRP nervosity" [21],[23],[24].

3.2.4. Intelligent production planning and control system (PPC)

The effective interaction of each system's data flow is the key to achieving integration. As shown in Figure 6, from the generation of production orders based on customer and material requirements to product quality inspection and packaging, there are numerous data interfacing and transmission needs that must be analyzed. The integration of intelligent information technologies can effectively reduce the complexity of data control. The key to realizing an intelligent production line is to drive production line scheduling by synthesizing the status information of each part of the data flow.

Production process data, which mainly originate from equipment and quality testing within the actual manufacturing process, have a crucial impact on product quality, as they ensure that the production process operates in a stable and efficient environment, stabilize operating time, and improve the overall production level. Therefore, intelligent production scheduling systems for the real-time management and control of diverse production data have been widely addressed by researchers. As shown in Figure 6, uncertainty in actual requirements and in the completion of each part of the production process affects effective completion and energy consumption. To cope with unexpected disruptions caused by uncertain factors in the production process, some researchers have developed job scheduling systems for disruption prediction; however, certain limitations in accuracy still exist [25].

On this basis, [26] developed an intelligent job scheduling system based on predictive scheduling and reflection, which mainly includes a statistical data analysis module, a database with a decision controller, and a predictive–responsive scheduling module. By analyzing the influence of uncertain factors such as job processing time and machine failures, feedback scheduling was achieved by combining designed scheduling rules such as FIFO (First-In, First-Out), EDD (Earliest Due Date), LPT (Longest Processing Time), and RND (Random). The robustness of the production scheduling system was improved through disruption prediction and the use of machine learning to manage subsequent scheduling. Furthermore, in a later study by Sobasek et al., a module based on the ARMA/ARIMA model was designed [27] to predict changes in processing time, which became an important part of the intelligent production scheduling system.

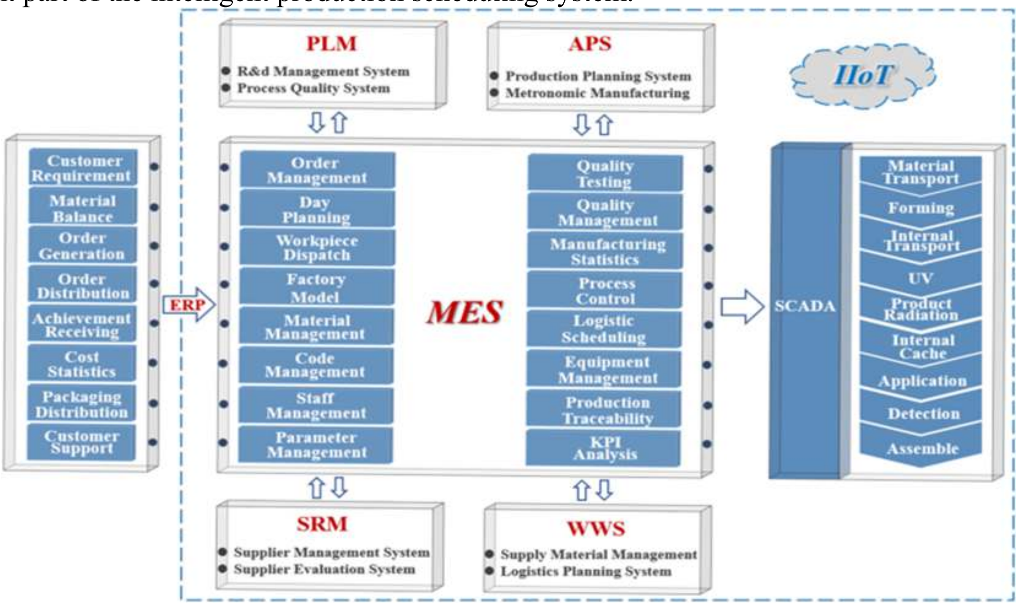

Figure 6. Framework of the Integrated Management Control System for Scheduling the Production of Complex Aerospace Components [28].

It is inevitable to encounter large and complex production tasks in manufacturing processes, which means that the amount of data processed by scheduling systems is also substantial. Wang in [28] constructed an integrated production planning and scheduling platform composed of a production planning and scheduling system, an Enterprise Resource Planning (ERP) system, and a Supervisory Control and Data Acquisition (SCADA) system. They achieved communication and integration of each module within the platform, including production plan management, process management, bill of materials, parts inventory management, and equipment management. Regarding system algorithms, top-down hierarchical decomposition of production tasks can be realized through a production task planning method based on the dynamic critical path method and the hierarchical task network method, which considerably reduces complexity. In addition, minimizing task completion time and maximizing equipment utilization can be achieved by adjusting hierarchical results of the process-level task optimization method based on the dynamic critical path and minimum idle time.

At the current stage, single-objective scheduling methods have demonstrated deficiencies in production scheduling processes based on multidimensional heterogeneous data interaction.

For research closer to real production processes, multi-objective scheduling is more practical due to its remarkable effectiveness in obtaining optimal or near-optimal solutions. Among various scheduling objectives, priority is given to minimum energy consumption, maximum completion time, and minimum total tardiness, indicating that reducing production costs and energy consumption, as well as improving efficiency, are the primary concerns of manufacturing enterprises and are consistent with the concept of green manufacturing [29]. To make optimal scheduling problems more comprehensive—that is, to obtain solutions that are more meaningful for practical production—additional objectives such as maximum machine load [30], optimal part sequencing [31], shortest delivery time [32], and system utilization rate [33] may also be considered. Visual inspection and real-time control of machine loading during production can ensure production safety and robustness. The ability to adjust part orders, delivery times, and system utilization as required is essential for cost savings and energy reduction. Moreover, the complexity of multi-objective production scheduling makes it difficult to find globally optimal solutions when many conflicting scheduling objectives exist. In such cases, the fuzzy satisfaction degree of a solution can be an effective means of evaluating its quality.

In multi-objective production scheduling problems, the main requirements for algorithms are high speed, high efficiency, and real-time adaptability to changing operating conditions. Due to local optimality and high computational time costs, traditional search algorithms cannot meet these demands. Scheduling rules are suitable for solving general scheduling problems in real production because of their low time complexity and stable scheduling capabilities [34]. However, in customized production of complex aerospace components with multi-variety and variable batch sizes, the influencing factors in scheduling optimization are more complex, which means that even the best scheduling rules are not guaranteed to cope with a wide range of unexpected situations [35]. Therefore, by designing customized scheduling rules for specific production situations in small-scale manufacturing, or by using heuristic algorithms to dynamically generate more appropriate scheduling rules to solve large-scale scheduling problems, satisfactory scheduling solutions can be obtained.

According to research, various heuristic algorithms have emerged in recent studies, demonstrating their importance in optimizing multi-objective production scheduling. Each algorithm has its own advantages and limitations, and different algorithms can generate complementary benefits. In other words, combining two or more optimization algorithms can effectively avoid the drawback whereby basic local search methods tend to fall into local optima when directly simulating natural processes. For example, the PSO algorithm and the simulated annealing algorithm can be combined to obtain PSO–simulated annealing algorithms, improved PSO algorithms, alternating PSO–simulated annealing algorithms, and collaborative PSO–simulated annealing algorithms. The solving capability of each hybrid algorithm results in better solution quality. Furthermore, with the popularity of high-performance computing devices and the rapid development of cloud computing, computational power is no longer the main factor restricting algorithm scalability; therefore, hybrid application of multiple heuristic algorithms can achieve more significant and richer optimization effects.

As mentioned above, scheduling rules and heuristic algorithms represent the primary starting point for solving multi-objective production scheduling problems. At the same time, benefiting from the development and integrated application of new technologies—such as advanced sensing technologies, information technology, and the Internet—the process of solving complex scheduling problems is further optimized. In manufacturing, using IoT as a basic platform for task scheduling can continuously integrate various control sensors with detection and monitoring capabilities, as well as mobile communication, intelligent analysis, and other technologies into all aspects of industrial production, thereby improving product quality, reducing resource consumption, and ultimately transforming traditional industry into a new stage of intelligence. More specifically, the Digital Twin can effectively reduce trial-and-error cost and time by constructing a virtual scheduling model. Edge computing ensures real-time performance and security of data-flow interaction in large-scale production scheduling scenarios. Due to their remarkable effects on cost reduction and production efficiency improvement, these two technologies are of great importance for the further development of customized manufacturing at this stage. In addition, Automated Guided Vehicles (AGVs) minimize delays and reduce costs in logistics systems and are widely used in complex material handling in smart factories [36]. Machine vision provides a new research perspective for the reliability of product conveyor systems [37]. Cloud computing supports real-time computing services for terminal devices to alleviate transmission pressure between the cloud and terminals [38].

Overall, in the face of complex processes such as aerospace component manufacturing, the ability of scheduling optimization algorithms to search for globally optimal scheduling schemes is limited. Intelligent information technologies can simplify complex problems and reduce the task search space, creating a favorable environment for solving optimization algorithms. Various intelligent information technologies can effectively reduce the complexity of multi-objective production scheduling problems, which is fully reflected in intelligent management control systems for production scheduling.

It is well known that multi-objective production scheduling is an NP-hard problem. According to the requirements of multi-batch and variable production, complex aerospace component manufacturing must simultaneously consider constraints related to energy consumption and temperature in hot-forming production, as well as methods for material preparation, tooling, and process sequencing. In other words, a complex production environment is formed under the coupling of multiple constraints. During the production process preparation stage, it is necessary to consider the pre-production of different job orders, such as mold, material, and furnace temperatures. During production, order delivery time, insulation temperature, and product delivery time should be included in process sequence considerations, as well as methods for handling unexpected events caused by workpiece material, mold lubrication effects, and other issues. Under the influence of multiple concurrent factors, it is necessary to integrate a production scheduling system with flexible logistics equipment to achieve continuous optimization of work tasks and obtain optimal cooperation of the production organization by analyzing trade-off relationships in objective quality testing. Therefore, intelligent management control systems for production scheduling play a key role in multi-objective production scheduling and promote the intelligent transformation and upgrading of traditional manufacturing enterprises.

Moreover, constructing intelligent production lines through further integration of intelligent information technologies with traditional manufacturing methods will be one of the most important features of future manufacturing modes, since cost optimization, energy consumption reduction, and efficiency improvement—derived from manufacturing intelligence—are precisely the objectives continuously pursued by manufacturing enterprises. However, data interaction and system arrangement remain difficult problems to solve.

Figure 7 clearly highlights the data flow and interaction among different levels of an intelligent production line. In addition to direct data flow transmission between systems, each system can read and download production-required data from information systems, including ERP, MES, and APS.

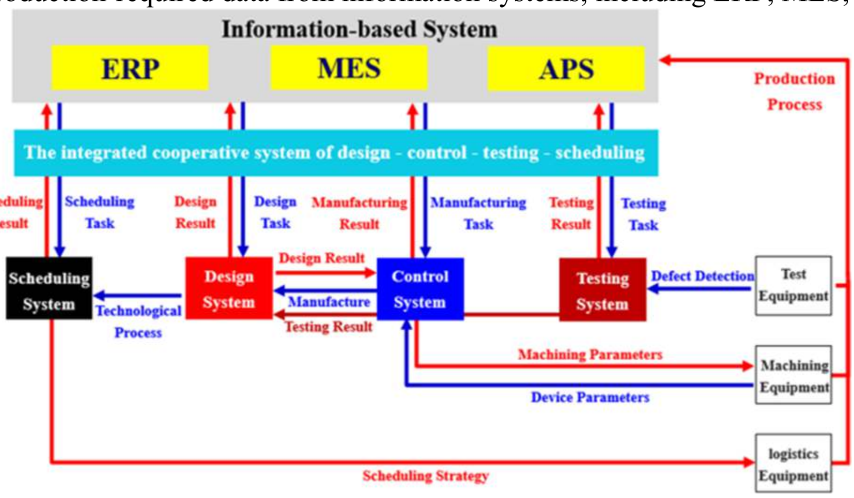

Figure 7. Data flow between systems in an Intelligent Production Line [25].

Regarding the intelligent production line for complex aerospace forged parts [39], the process flow designed by the CAPP system, process cases successfully verified through quality testing, and abnormal conditions detected by the process control system can be transmitted to the scheduling management control system for dynamic production rescheduling, thereby achieving optimal coordination of production organization. It can be observed that production scheduling optimization is the key technology of the overall production process, and the intelligent management control system for production scheduling is an indispensable part of the intelligent production line.

3.2.2 The KANBAN system

The KANBAN system is considered a tool designed for managing production flows. It supports the creation of a *pull* system, based on the fourth fundamental principle of Lean Management. It enables flexible and organized communication between factory sectors, forcing the downstream sector to indicate to the upstream sector what must be produced and in what quantities [40]. It can be used as a production planning and control tool in assembly production systems, where the demand for components depends on market demand for the final product [41]. Consequently, the Kanban system tends to be implemented in organizations that produce to order and seek flexibility as part of their organizational capabilities [42].

This type of system was originally developed for deterministic production environments with stable demand and processing times. However, demand uncertainty is increasingly prevalent in today's context, and there may be a need to adjust the number of Kanban cards in the production system according to demand variation. This has led to the development of dynamic or flexible Kanban systems, rather than fixed-card Kanban systems used in environments with stable demand [43], [44].

In its most commonly used form, Kanban is a system that employs so-called *supermarkets* or controlled inventory locations, which are replenished based on cards. These cards signal which components have been consumed and the quantities that require replenishment [41]. This contributes to the control of intermediate inventories, avoiding overproduction and preventing stocks from falling below minimum levels [45]. Other advantages include simplicity in production planning, reduced workload for operators, ease of component identification through the Kanban card attached to containers, and a substantial reduction in bureaucracy [43].

Gross and McInnis [46] suggest seven steps for the proper implementation of a Kanban system. The first step involves collecting the data necessary to characterize the process and make fact-based decisions. The Kanban size is calculated in the second step, taking into account current system conditions. The number of Kanban cards associated with a specific component depends on demand, lead time, safety stock, and container capacity [44]. Subsequently, rules for information and material flows are established, resulting in an implementation plan. In the fourth step, the design and its rules are presented to the team, which performs several simulations, if possible. The team then verifies whether all conditions for starting Kanban are met. In the final two phases of the process, auditing and maintenance are carried out, monitoring system progress and checking whether it meets requirements. Potential system improvements are identified and analyzed [47].

4. Smart Factory in Romania

There are many factors that place Romania in a highly favorable position with regard to the transition to Industry 4.0, and even Industry 5.0. Below are some of Romania's key advantages:

- *Make-to-order production*. It is assumed that the automotive industry will generate the greatest resources and make the largest investments. Fortunately for Romania, this industry has experienced strong growth in recent years. The number of automotive suppliers in Romania is continuously increasing. Although there are only two automotive manufacturers—Dacia and Ford—the supplier network is well developed (Hella, Contitech, Continental, Bosch, Valeo, Mahle, Autoliv, Honeywell, etc.). Of the world's top 20 automotive suppliers, 13 are present in Romania with production facilities. According to ACAROM, the turnover of suppliers is twice as high as that of vehicle manufacturers in Romania [2].

- *New suppliers for cyber-physical systems*. IT companies will play a major role, as Industry 4.0 will attract new providers of cyber-physical systems (CPS) or services into industrial production, such as IT security, Big Data analytics, machine-to-machine (M2M) solutions, and artificial intelligence. The IT sector is highly developed in Romania and can support investors' efforts in digital factories [2].
- *Internet connection speed*. Romania's internet connection speed is among the highest and most performant in the world. The Internet of Things will generate vast amounts of data and will therefore require very high speeds for data transfer and processing [2].
- *Skills in Romania*. The competencies required for digital factories are available in Romania due to a very large market for IT specialists. There is a strong manufacturing tradition and reputable technical universities, as evidenced by the numerous investments in research and development centers in the automotive sector [2].
- *Grants for Romania*. In the coming period, there will be numerous non-reimbursable funding programs for research and development in the fields of Industry 4.0, Industry 5.0, and digitalization technologies [2].
- *External partners*.

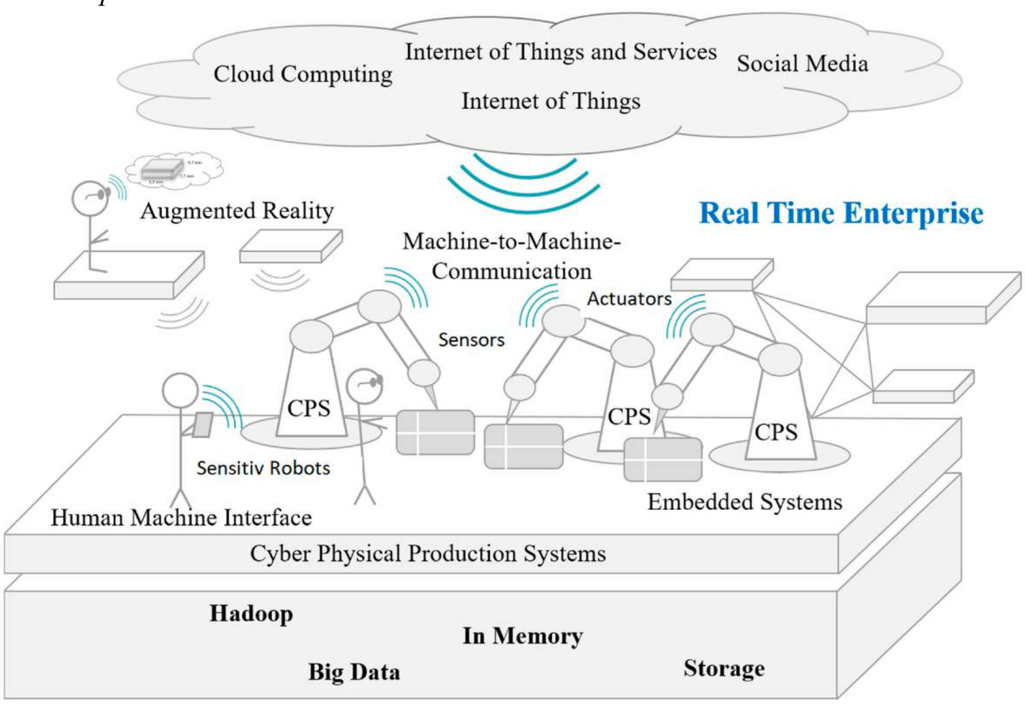

Figure 8. Terminologies used in Smart Factories [48].

Germany is one of the main supporters of the *Industry 4.0* and *Smart Factory* concepts and is among the largest investors in Romania. Many German companies already operate state-of-the-art technologies in their Romanian production facilities (Figure 8). There are significant development opportunities for Romania in the context of Industry 4.0 and even Industry 5.0 [48].

5. Conclusions

This paper examined the main concepts, methods, and systems used in production planning and control in the context of the transition toward Smart Factories and Industry 4.0. The analysis shows that current manufacturing environments require increased flexibility, higher transparency of processes, and rapid adaptation to changing market conditions, characterized by variable demand, short delivery times, and growing product customization.

The comparative assessment of MRP/MRP II, ERP, MES, Kanban and intelligent PPC systems highlights that no single system can independently meet all the requirements of modern production. Therefore, the integration of strategic, tactical and operational planning levels, as well as the continuous exchange of data between information systems and shop-floor equipment, is essential for efficient production control.

The study underlines the important role of MES systems in discrete manufacturing, acting as the interface between planning and execution. Real-time data collection and monitoring allow faster reactions to disturbances, reduce downtime, improve product quality and support more efficient use of resources. At the same time, ERP systems remain critical for coordinating business processes and supporting medium- and long-term production and resource planning.

The results also indicate the limitations of traditional planning approaches based on fixed lead times and rigid forecasts, especially in environments affected by demand uncertainty and resource constraints.

This highlights the need for adaptive planning methods and intelligent decision-support mechanisms.

In this context, intelligent production planning and control systems, supported by multi-objective optimization, heuristic methods and advanced digital technologies such as the Internet of Things and Digital Twin, represent a key direction for the future development of manufacturing systems. These solutions improve scheduling robustness, reduce decision complexity and enhance system responsiveness.

An important conclusion is that modern production planning must simultaneously consider multiple objectives, including delivery performance, energy consumption, equipment utilization and product quality. Consequently, multi-objective optimization and intelligent support systems become indispensable for effective production management.

Finally, the analysis of the Romanian industrial context shows that favorable conditions exist for the adoption of Smart Factory solutions, supported by the IT sector, communication infrastructure and industrial tradition. However, successful implementation requires further efforts in system integration, data standardization, workforce training and organizational change

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