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CONDITIONS FOR THE APPLICATION OF A GENETIC ALGORITHM IN SCHEDULING PRODUCTION ORDERS IN AN INDUSTRY 4.0 ENVIRONMENT

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Purpose: The article is based on the premises of the R&D project "Research and Development Work on the Development and Application of a Genetic Algorithm for the Optimization of Production Management." The primary goal was to determine the conditions for the application of genetic algorithms in the scheduling of production orders in the Industry 4.0 environment.
Design/methodology/approach: The objectives are achieved through a comprehensive analysis of current challenges in production management, particularly in the context of Industry 4.0. The main method used is a theoretical examination of the potential applications of genetic algorithms (GAs) in optimizing production scheduling. The approach is interdisciplinary, combining insights from artificial intelligence, operations management, and industrial engineering. The paper explores both the theoretical framework and practical aspects of GAs in the production environment.
Findings: The paper finds that genetic algorithms can significantly enhance production scheduling in the dynamic and complex environment of Industry 4.0. GAs offer solutions for optimizing production processes, maintenance prediction, and supply chain management. It was also found that while the practical applications of GAs are still developing, they hold great potential for addressing the multifaceted challenges of modern production systems.
Research limitations/implications: The research is primarily theoretical, suggesting a need for empirical studies to validate the proposed applications of genetic algorithms in real-world industrial settings. Future research should focus on case studies and simulations to demonstrate the effectiveness of GAs in production scheduling.

Practical implications: This research highlights the potential of genetic algorithms to revolutionize production scheduling in Industry 4.0, leading to increased efficiency, reduced costs, and enhanced production flexibility. Businesses could implement GAs to optimize various aspects of production, leading to significant economic benefits.
Social implications: The implementation of genetic algorithms in production can influence society by potentially leading to more sustainable production practices, efficient use of resources, and reduced environmental impact. It could also set new industry standards in production management, influencing public attitudes towards technological innovation in manufacturing.
Originality/value: The originality of the paper lies in its comprehensive analysis of the application of genetic algorithms in the context of Industry 4.0, a relatively new and unexplored area. The paper's value is in providing a theoretical foundation for future empirical research and practical implementation, and it is addressed to academics, industry professionals, and policymakers in the field of production management.

Keywords: Genetic Algorithms, Industry 4.0, Production Scheduling, Optimization, Manufacturing Management.

Category of the paper: Theoretical Research, Applied Research.

Introduction

The manufacturing industry has undergone dynamic changes in recent years. On one hand, the consumer market encourages manufacturers to expand their product range by introducing a growing number of small differentiators or product variables, and to seek and introduce innovative products. On the other hand, market globalization brings local companies to international markets while introducing global products and brands that compete for customers not only with product appeal but also with price. This leads to numerous changes in the management of manufacturing companies. Producers, fighting for the best material supply prices, often have to choose between quality and delivery punctuality. At the same time, all management trends are moving towards reducing inventory and associated costs. On the other side, we have the customer who expects quick turnaround times at competitive prices and immediate responses about planned delivery dates. Balancing customer interests with receiver expectations is increasingly challenging within the framework of traditional production planning due to the growing number of variables affecting production plans. The wide variety of products is associated with the need to arrange many variants of production batches, considering setup times, which in combination with logistical deadlines and production capabilities (availability of machines and personnel) expands the possibilities of arranging the production plan into countless combinations. Traditional software is unable to cope with a large number of variables and determinants in a satisfactory time. The tools used in the market for arranging production plans are so complicated or time-consuming that in case of any disturbances such as delayed material delivery, machine breakdown, or the impact of a priority order, most companies rely on the intuition of planners or production managers.

The main objective of this study is to present the concept of the use of genetic algorithms in the problems of Industry 4.0, and in particular in the processes of production planning and scheduling. Industry 4.0 encompasses technologies such as cyber-physical systems, IoT, Big Data analytics, artificial intelligence, as well as issues related to production planning and scheduling systems, including simulation, adaptive structure of the production process, and vertical and horizontal integration. Therefore, the above-mentioned issues should be taken into account in the considerations, and this in turn requires their adaptation and flexibility both in planning and in the approach to production scheduling, taking into account dynamic changes in the production process and the increased level of uncertainty.

The main research method was bibliometric analysis of scientific documents (scholarly works) related to the keywords "genetic algorithm", carried out using the lens.org service.

The considerations have led to the development of assumptions for preparing a project application titled "Research and development work concerning the development and application of a genetic algorithm to optimize production management".

Genetic Algorithms

Genetic algorithms (GA) are a type of optimization algorithms inspired by the process of natural selection. They are widely used in the field of artificial intelligence, particularly in machine learning and robotics, and have gained significant attention in the context of Industry 4.0. This article discusses the applications of genetic algorithms in Industry 4.0 production and how they can be used to optimize industrial processes. One of the main applications of genetic algorithms in Industry 4.0, as mentioned earlier, is the optimization of production processes. GAs can be used to find optimal parameters for a given process, such as temperature or pressure, by evaluating a set of potential solutions. This allows for more efficient and economical production, as the process can be adjusted to reduce waste and increase efficiency. Additionally, GAs can be used for product or component design optimization, leading to more efficient and economical production. Another application of genetic algorithms in Industry 4.0 is predictive maintenance. GAs can be used to analyze historical data and predict when a machine or component is most likely to fail. This allows for proactive maintenance, reducing downtime and increasing efficiency. GAs can also be used to optimize maintenance schedules, ensuring that resources are allocated in the most effective way. Additionally, GAs can be used to optimize supply chain management. By analyzing historical data and current market conditions, GAs can be used to optimize inventory levels, transportation routes, and production schedules. This can lead to significant cost savings and more efficient product delivery to customers (Hu, Feng, 2018; Hwa, Yan, Chao, 2020; Sun, Chen, Zhou, 2020). Genetic algorithms have many applications in Industry 4.0, including optimizing production processes, predictive maintenance, and supply chain management. They offer a powerful tool for optimizing industrial processes and improving efficiency, leading to cost savings and increased productivity.

Genetic Algorithms in Literature

A bibliometric analysis of scholarly works related to the keywords "genetic algorithm", conducted using the lens.org service, indicates that the first publications on this topic appeared in the 1970s. A total of over 320,000 publications on this topic have been indexed on lens.org since 1966. A significant increase in the number of publications, and thus in the interest of researchers in the topic of genetic algorithms, occurred in the 1990s, with a peak in 2015, in which nearly 25,000 publications on genetic algorithms were published. The analysis of patents for the keywords "genetic algorithm" conducted using lens.org indicates a steady and dynamic increase in patent activity in this field. However, it should be noted that the patenting of computer programs is only possible in American jurisdiction. Of the over 46,000 documents (patent applications and patents), more than half (27,000) are American documents. The systematic increase in the number of patents compared to the stable situation related to scholarly publications means that genetic algorithms are currently in the phase of implementing practical solutions in various fields of activity. The applied solution will essentially be a hybrid genetic algorithm (HGA), i.e., one that uses local search procedures within the obtained generation of solutions. The literature describes various problems with the application of hybrid genetic algorithms, e.g.: flow shop scheduling problem, job shop scheduling problem, the problem of assigning limited work resources to task implementation, project implementation problems under limited resource conditions (Vallsa et al., 2008), problems in medical diagnostics of diseases (e.g., markers and other methods of searching large sets of medical data). The total number of scholarly publications for the keywords "hybrid genetic algorithm" indexed on lens.org is 5,671. In terms of patents, lens.org for the keywords "hybrid genetic algorithm" indicates only 7 documents (5 applications and 2 obtained patents):

1. Application of Cost Constraints in Event Scheduling (application).
2. Genetic Severity Markers in Multiple Sclerosis (USPTO application).
3. Genetic Severity Markers in Multiple Sclerosis (WIPO application).
4. Systems and Methods for Predicting Repair Outcomes in Genetic Engineering (WIPO application).
5. Application of Cost Constraints in Event Scheduling (USPTO granted rights).
6. Genetic Severity Markers in Multiple Sclerosis (Australian application).
7. Genetic Severity Markers in Multiple Sclerosis (EPC granted rights).

The above summary indicates a limited (so far) nature of practical applications. Noteworthy is the only patent in the above set related to the problem of event scheduling.

Division of Basic Production Scheduling Problems

Production planning in systems: The job shop problem, flow shop problem, and open shop problem are examples of optimization problems in industry and production. These problems involve determining the order and timing of tasks or operations, aiming to minimize production time, reduce costs, and increase efficiency.

In the job shop scheduling problem, a set of tasks must be processed on a set of machines, with each task requiring a specific sequence of operations on different machines. The goal is to minimize the total time, i.e., the time needed to complete all tasks. This problem is NP-hard, meaning that finding an optimal solution requires exponential time. Various algorithms have been proposed to solve this problem, including genetic algorithms, simulated annealing, and ant colony optimization (Baker, 1974; Das, Mohapatra, 2001).

In the flow shop scheduling problem, a set of tasks must be processed on a set of machines in a fixed order, with each task requiring the same sequence of operations on all machines. The goal is to minimize the total time, similar to the job shop scheduling problem. This problem is also NP-hard, and various algorithms have been proposed for its solution, including dynamic programming, genetic algorithms, and simulated annealing (Elmaghraby, 1975; Panwalkar, Sarin, 1984).

In the open shop scheduling problem, a set of tasks must be processed on a set of machines, with each task requiring a specific sequence of operations on any machine. Unlike the job shop and flow shop scheduling problems, the sequence of operations for each task can be different on each machine. The goal is again to minimize the total time. This problem is also NP-hard, and various algorithms have been proposed for its solution, including branch and bound, simulated annealing, and genetic algorithms (Adams, Balas, 1984; Pinedo, 2012).

Among the mentioned problems, the flow shop (flow-shop) is one of the basic problems in production scheduling. As mentioned, this problem is related to the order of jobs (n) on machines (m). Searching for solutions to this issue can be divided into permutation problems with a solution space of n! and non-permutation flow-shop problems with a solution space of n!(m-1). In both cases, solving this problem is classified as an NP-hard task as mentioned earlier. The space of possible solutions from which any could be the optimal solution dramatically increases with the size of the task. Beyond a certain configuration, searching all permutations becomes utilitarianly inefficient.

Industry 4.0 and Challenges in Planning and Scheduling Production

Industry 4.0 can be understood as the comprehensive digitalization and interconnection of production and logistical processes covering the entire product life cycle, from product and service design, customer order handling, product manufacturing, delivery to the point of consumption, to post-sales service, including activities within reverse logistics (Stawiarska et al., 2021). In such a case, Industry 4.0 is based on three main pillars: digitalization of the product offering (including service offerings), introduction of innovative digital business models, and digitalization and increased vertical and horizontal integration of value chains (Matusek, 2021).

Cyber-Physical Systems (CPS)

CPS is defined as the integration of physical elements of the production process (such as machines, robots, people), capable of collaboration (including machine-to-machine and human-robot collaboration), along with integrated sensors and monitoring instrumentation, which collect data about the state and processes generated during task processing (Frank et al., 2019). The use of data collection systems or monitoring technologies goes hand in hand with the need for a system capable of processing a large number of events and capable of efficient analysis of large amounts of data (Friedemann et al., 2016). As the effectiveness of environmental monitoring increases, so does the number of sensors in the production process, and thus the requirements related to the ability to process collected data increase. From a scheduling perspective, this creates conditions for their development towards real-time and reactive scheduling (Lai et al., 2018; Zhang et al., 2018). At the same time, some authors (e.g., Nahhas et al., 2018) emphasize the need to consider decision-making at the tactical and strategic levels, which should also be included in the real-time scheduling process. In such cases, they encompass a wide range of decisions from automatic planning of maintenance activities to reactive adjustment of the schedule in response to unforeseen events (e.g., sudden, urgent customer orders or unpredictable delays in material deliveries, machine breakdowns). As a result, increased flexibility in a greater number of organizational dimensions is expected, strengthening the vertical integration of machines and production processes. The need for flexibility is not only a result of a broader scope and newly available information. It also arises from the "proactive" feature of devices, which involves their autonomous decisions concerning, for example, the order of operations to be included in schedules based on data collected from other devices and the environment (Uhlemann et al., 2017). Current machines, in most cases, can only receive commands and react to them, while CPS should be able to actively suggest task distribution and adjust operation parameters to maximize productivity, task completion time, etc. (Lee et al., 2013).

However, already known applications of intelligent algorithms capable of learning show some limitations in handling unexpected events, preventing their widespread implementation in industry (Bagheri et al., 2015). This translates to another, already evolving direction in scheduling methods, referring to the fact that a large amount of significant information, combined with new interactions between machines and people, generates a series of new constraints that must be taken into account during the scheduling process (Lödding et al., 2010). In other words, task and resource management will need to consider various trade-offs, taking into account these new interactions of collaborating units (i.e., people and machines) (Klement et al., 2017; Benkamoun et al., 2015). This imposes the necessity to consider new objective functions and/or appropriate constraints to ensure the smooth flow of orders in the production process. One of the important constraints arises from the technological limitations of intelligent sensors and monitoring technologies (sometimes the reliable functionality of these systems is disturbed in many cases due to environmental conditions, such as the presence of water or large quantities of metal devices (Huang et al., 2011).

In such a situation, planning under uncertainty and dealing with missing data will most likely become a key issue in schedule building (Fu et al., 2018; Guendouz et al., 2017; Huang et al., 2011). While many scheduling methods are effective in the case of known parameters of the production system, in practice it is not always possible to definitively determine its state. Since even humans have difficulty making decisions with incomplete information, scheduling should include mechanisms/rules capable of considering such situations, which will ultimately contribute to improved decision-maker support (Azman et al., 2020).

Internet of Things (IoT)

The Internet of Things (IoT) is understood as physical objects (or groups of such objects) equipped with sensors, capable of processing information, software, and other technologies, which connect and exchange data with other devices and systems via the Internet or other communication networks (Stawiarska et al., 2021). It is noteworthy that devices do not have to be connected to the public Internet, it is sufficient that they are connected to a network and are uniquely (individually) identified. In this sense, IoT not only connects partners, competitors, and customers, but also production process units (e.g., machines and employees) and decision-makers. IoT enables the functioning of so-called product-service systems (Matusek, 2023), in which customers are in constant contact with manufacturers and suppliers through networks (e.g., the Internet), placing orders and providing feedback, which ultimately facilitates mass customization of products (Matusek, 2023; Kerin, Pham, 2019). For this reason, product-service systems have been included in the scope of IoT, thus renamed the Internet of Things and Services (IoT&S). Mass customization requires flexible scheduling capabilities. Hence, it is necessary to enable the adaptation of schedules to different product portfolios, as well as enabling continuous reactive corrections to adapt to sudden changes in demand or urgent orders. Considering the complexity of these requirements, research related to decentralization, and in particular to autonomous decision-making, is considered a key means to solve scheduling problems, providing decision-makers and production process units with information that allows them to autonomously make their own decisions (Rüßmann et al., 2015; Brettel et al., 2017). In such an environment, it is natural that scheduling concepts guaranteeing the greatest flexibility will gain an advantage over others, i.e., conventional or predictive ones (Hsu et al., 2011).

Vertical and Horizontal Integration

Vertical integration of partners and suppliers in the supply chain means that scheduling is also directly related to the increase in significant and immediately available information, but this time concerning products, demand, payment terms, or availability/delays in resource availability. Mass customization intensifies these phenomena (Erol, Sihn, 2017). This can prevent problems associated with traditional, centralized scheduling, which is rarely up-to-date after considering occurring deviations. Such a situation usually results in high inventory levels or carrying out non-value-adding activities, as components and raw materials are delivered too early or too late (Brettel et al., 2017). Additionally, this large amount of information and data, which becomes available as a result of vertical integration, creates opportunities for the application of big data technologies (Matusek, 2023; Lee et al., 2013). Big data collected from production processes, exploration of such data, and then transforming it into useful knowledge can be useful in supporting the adaptability of plans and schedules.

On the other hand, horizontal integration refers to the connectivity between all elements that make up the product life cycle in an organization through the close inclusion of activities in marketing, design, engineering, production, and sales, along with the activities of other companies in a horizontal arrangement. Ultimately, this transforms the production process into a dynamic market of customers, where resources are combined between companies and configured to execute various product variants. Consequently, this translates into dynamic scheduling (Karnik et al., 2022). Both horizontal and vertical integration involves collecting as much available information as possible, which can be used to improve the quality of schedules. In this case, this information can be targeted at increasing the accuracy and reliability of schedules, as they also consider issues such as delivery delays (i.e., of raw materials, components) or variability in supply and demand.

Adaptive Production Process Structure and Simulations

The dimension of "simulation", as proposed by Rüßmann et al. (2015) in the context of Industry 4.0, can be incorporated into a broader concept, i.e., Adaptive Manufacturing. Along with the digitalization process (digital twin), it can be used for analyzing various scenarios and the impact of events on the production process and for decentralized decision-making. While CPS primarily concerns the physical elements of the production process and the associated sensors and monitoring instrumentation, Adaptive Manufacturing pertains to the virtual counterpart of these physical resources, whose behavior is modeled using simulation systems based on data collected from the process monitoring system (Nahhas et al., 2018).

A major identified limitation of the adaptive structure of the production process is the difficulty in optimizing in environments of such high complexity while considering a large amount of available data. This is related to the challenges of expanding the optimization system to include the ability to decompose scheduling problems. The success of optimization, in this case, largely depends on the ability to decompose a large problem into subproblems while achieving a solution close to the global optimum (Mönch et al., 2011). This idea leads to adopting a decentralized approach to decision-making, both at the strategic and operational levels. A decentralized approach would provide an environment for autonomous decision-making, directly controlled by elements of the production process instead of a centralized controlling unit. This increases the flexibility and agility of production. The level of decentralization can vary, starting from partial processing of collected data by sensor-equipped machines. In this case, only a small portion of pre-processed data remains accessible to the central controlling unit and/or other devices (a solution known as Fog or Edge Computing). Ending with the full processing and interpretation of all collected data by the local devices themselves (Mo et al., 2019). Such an approach allows for the use of decision rules that require less computing power and data processing time. Thus, optimal decisions are limited to the local scope of the device's actions, increasing the schedule's resilience to disturbances (Rawat et al., 2017). However, the evolution of scheduling towards decentralized and autonomous decision-making leads to a situation where global optimization solutions become a complex issue (Zhang et al., 2019). If each resource makes its own decisions based on local data, increased effort is required for their coordination, as each tries to achieve its own goals, which may not necessarily be aimed at the global optimization of the system. Therefore, for a decentralized scheduling system to be effective, it is necessary to align the goals of individual units, allowing them to collectively achieve the goal of the production system.

In summary, to fully utilize the potential of Industry 4.0 technologies, production planning and scheduling software must utilize the vast amount of data generated in the production process, easily integrate, leverage new technologies supported by Industry 4.0, and automatically adapt to the continuous changes occurring in the production process. The complexity of production systems continues to grow with the pace of implementing new technologies and the new possibilities they bring for manufacturers (e.g., mass customization of products, change in business models). This requires the construction of schedules with a high degree of adaptability, flexibility, reconfigurability, and resilience to an increased level of uncertainty.

Key Considerations for Implementing Genetic Algorithms in Industry 4.0 Production

The application of genetic algorithms for scheduling production orders in an Industry 4.0 environment involves various considerations that need to be taken into account to effectively utilize the potential of this technology. Among the key considerations highlighted in this article are:

- Complexity of the production environment, indicating that Industry 4.0 is characterized by complexity stemming from the integration of cyber-physical systems, IoT, Big Data, AI, and other technologies. Therefore, genetic algorithms must be capable of processing and analyzing large amounts of data for effective management of complex production processes.
- Flexibility and scalability of algorithms, suggesting that GAs should be adaptable to dynamic changes in production, enabling quick reconfigurations in response to changing market conditions, consumer demand, and resource availability.
- Integration with existing production and IT systems, requiring compatibility and the ability to cooperate with various technological platforms.
- Data management and privacy, meaning that in the context of Industry 4.0, where huge amounts of data are collected, it is essential to ensure data security and protection, as well as proper data management for the effective use of genetic algorithms.
- Consideration of human and organizational factors, as besides technological aspects, it is important that the implementation of genetic algorithms takes into account factors such as employee training, technology acceptance by staff, and changes in organizational structure.
- Resilience to disruptions, indicating that systems using genetic algorithms should be properly designed to be resistant to hardware failures, delivery delays, or sudden changes in orders.

Furthermore, other important considerations for implementing genetic algorithms for scheduling production orders in an Industry 4.0 environment include:

1. Before full implementation, genetic algorithms require detailed testing and optimization to ensure they are effective and efficient in solving real-world production problems.
2. Genetic algorithms should support decision-making processes at various management levels, providing decision-makers with necessary information for making informed and efficient operational and strategic decisions.
3. Implementing genetic algorithms requires an innovative approach and readiness to adapt new technologies, which may necessitate a change in organizational culture and approach to innovation.

4. The Industry 4.0 production environment is dynamic and continuously evolving, so genetic algorithms must be regularly evaluated and improved to keep up with changing needs and trends.

Considering these conditions, the implementation of GAs requires addressing the following issues:

- Whether the implemented solution complies with regulations, referring to the specificities of industrial sectors, which have various regulations regarding quality, safety, and environmental protection that must be considered in the planning proces?
- Whether employees in the enterprise have the necessary skills to work with advanced IT tools, as well as the ability to interpret results generated by the algorithm?
- Whether employees and management are open to implementing new technologies and the changes these technologies bring to production processes?
- How to ensure data security and privacy, meaning that robust security measures must be implemented to protect production and personal data from unauthorized access and cyber attacks?
- How to consider ethical and social aspects of using GAs, as the implementation of advanced technologies like genetic algorithms can raise concerns about the impact on employment and the role of workers in an automated environment?

Summary

The article presents the complex conditions for the application of genetic algorithms in scheduling manufacturing orders in the context of Industry 4.0. The changing dynamics of the manufacturing industry, characterized by an increasing assortment diversity, require manufacturers to adapt to rapid changes, maintain flexibility, and be efficient in production. In such an environment, traditional production planning methods are not sufficiently effective, especially in the face of an increased number of variables affecting the production process.

Genetic algorithms, inspired by natural selection processes, have the potential to optimize production processes in the context of Industry 4.0. These algorithms are used to solve optimization problems in industry, especially in production scheduling, which is related to the aim of minimizing production time and costs while increasing efficiency.

The steadily growing number of patents related to genetic algorithms, particularly in the American jurisdiction, indicates their practical applications and commercial significance. However, despite the increasing interest in genetic algorithms, the number of patents concerning hybrid genetic algorithms is relatively small, which may indicate some limitations in their practical application.

A bibliometric analysis conducted using the lens.org service showed that various forms of genetic algorithm applications are considered in the literature, including hybrid genetic algorithms that integrate local search procedures for more effective problem-solving in production. These applications can cover a wide range of issues, from optimizing production processes to more complex issues such as task and resource management in the context of new interactions between machines and people.

The context of Industry 4.0, encompassing technologies such as cyber-physical systems, IoT, Big Data analytics, artificial intelligence, and others, sets new requirements for scheduling systems. This requires adaptation and flexibility both in planning and in the approach to production scheduling, taking into account dynamic changes in the production process and increased levels of uncertainty.

Genetic algorithms, with their ability to work efficiently in complex and dynamically changing environments, seem to be an effective tool in developing new scheduling methods in Industry 4.0. Their application can help address challenges associated with mass product personalization, vertical and horizontal integration of supply chains, and the need to quickly respond to changing market and production conditions.

In conclusion, genetic algorithms have great potential in contributing to more effective and flexible management of production processes in the era of Industry 4.0, which can lead to better efficiency, reduced costs, and increased productivity. However, there is still a need for further research and development to fully utilize their potential in practice. Therefore, the considerations presented in this article served to develop the assumptions of a project application titled "Research and development work on the development and application of a genetic algorithm to optimize production management". This application has been approved for implementation in the years 2021-2023.

Nevertheless, it is worth pointing out the numerous conditions for the application of the genetic algorithm to schedule manufacturing orders in the Industry 4.0 environment to effectively utilize the potential of this technology. The article highlights the complexity of the production environment, the flexibility and scalability of algorithms, integration with existing production and IT systems, data and privacy management, consideration of human and organizational factors, and resilience to disruptions.

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