Systematic Literature Review of Artificial Intelligence in production scheduling problems in real cases

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Abstract: Industry 4.0 has revolutionized the scheduling problem by providing real-time data availability, predictive maintenance capabilities, optimization algorithms, flexibility, integration of supply chain data, and collaborative platforms. These advancements empower schedulers to make data-driven decisions, adapt to changes more efficiently, optimize resource allocation, and improve overall scheduling effectiveness. As a result, companies can enhance their operational efficiency, reduce downtime, and gain a competitive edge in the market. Consequently, scheduling AI algorithms can play a significant role in enhancing a company competitiveness in today fast-paced business environment with their related benefits. In this context and for this purpose, the European project AIDEAS 'Fabrication Optimiser' tool wants to realise an AI-based scheduling tool. Therefore, the first step to its realisation was to define the state of the art. In literature, there are several contributions on using artificial intelligence to solve production scheduling problems. The first search was conducted on Scopus database selecting the years 2011 to 2022 and considering only publications in the field of engineering. Since Neural Networks and Particle Swarm Optimization are the most widely used strategy for solving such problems, this study aims at analysing how authors solve real production scheduling problems, in what context and what benefits they have obtained. The results of this study show how neural network and particle swarm optimization allow for solving different types of multi-objective and single-objective programming problems in dynamic production environments while generating benefits for the company according to their needs.

Keywords: Artificial Intelligence; Scheduling problem; Neural Networks, Particle Swarm Optimization; Machine learning.

I. INTRODUCTION

The spread of Industry 4.0 paradigms, the development of increasingly intelligent factories, and the use of smart sensors and connectivity between the different parts of a company have led to an increasing body of literature on the use of Artificial Intelligence (AI) in manufacturing systems, which has been growing faster and faster in recent years. Modern manufacturing environments are subject to multiple factors that influence the manufacturing process like machine breakdowns, variations of the orders production, random job arrivals, etc. To be competitive in the actual context is important to be flexible and be able to respond faster to variations in production planning [1]. Currently, production procedures are dynamically changed to actively satisfy consumer wants and create a wide range of low-cost products. To this purpose, the manufacturing ecosystem of today is distinguished by a reduced product life cycle, a high level of product variability, and an escalating level of international competition. Artificial intelligence is an important instrument in the context of manufacturing systems to respond fast and predict future anomalies in the production plan; the AI instrument can be used as support of decision-making process; in literature, there are a lot of contributes about the use of AI instrument to realize dynamic scheduling [2] algorithms or algorithms able to find difficult correlations between factors in the manufacturing environment.

The development of a dynamic scheduling programme based on AI is the major objective of the European project AIDEAS's "Fabrication Optimiser" tool, which was born in this context. Consequently, examining how other authors had addressed similar challenges was essential. This paper has a twofold objective:

- Understand what the tendency is to solve scheduling problems through the use of AI and what AI techniques are most widely used in the literature
- Analyse how other authors solve production scheduling problems in real cases and see what advantages they have achieved.

Thus, a systematic literature review was conducted using the Scopus database and bibliometric tools such as VOSviewer [3].

The scheduling problem is a classic NP-hard problem [4] and is also one of the key links for the efficient operation of an intelligent production system, because dynamic scheduling can optimize several KPIs in production space, for example, reduce the tardiness, the cost of storage, makespan, traveling time and others KPI that change from company to company. Intelligent production gave numerous advantages in terms of flexibility, maintainability, and cost. In fact, artificial intelligence is not used only for dynamic scheduling but is used in production plans to help in the decision-making process.

The dynamic nature of the manufacturing systems implies the necessary adoption of a dynamic scheduling paradigm to deal with unforeseen events that disrupt the execution of a schedule as the assigned apparitions can be immediately redirected to other machines. According to [5], there are three major manifestations of dynamic scheduling in AI literature: task re-scheduling concerns the reprogramming of a specific activity within the production process as a reaction to an interruption in the original program. Resource allocation especially in flexible shop floors where the use of AI should improve the ability to allocate resources to deal with plan disruptions and line balancing after any interruptions in the production process.

In this paper, Section 2 explains how the research was conducted and which tools were used to study publication trends, and which AI techniques are most prevalent in the literature. In Section 3, relevant contributions found in the literature are reported. Section 4 provides discussions, future development, and a conclusion.

II. Method and Data

Figure 1 shows the steps taken to carry out the literature review. In the following sections, all these steps are explained in detail.

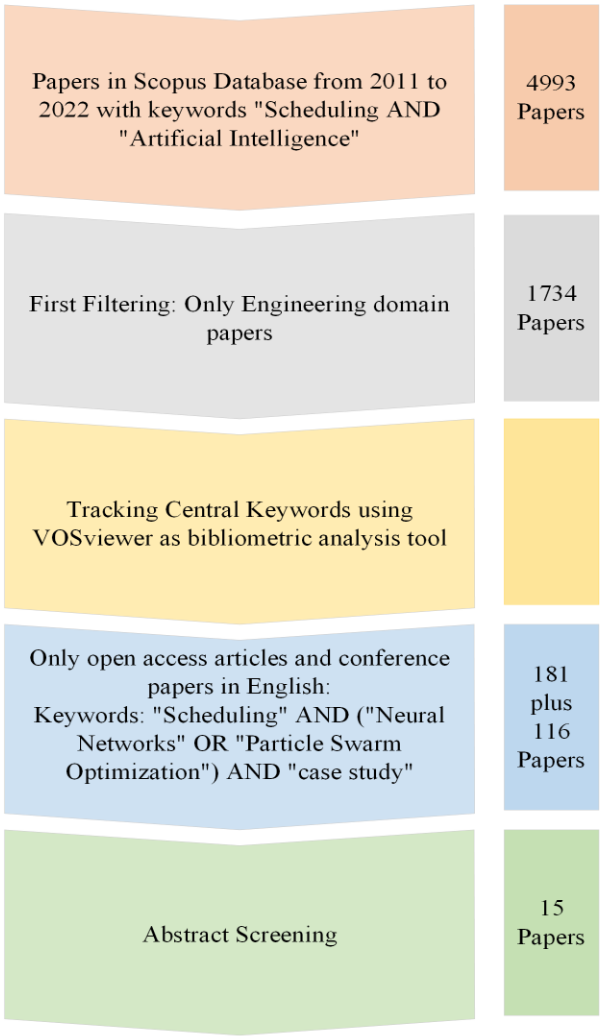

Figure 1 Framework on research activities

A. *Preliminary Research*

The literature search is set using Scopus as a database and searching for articles, conference papers and reviews, reviews, and book chapters in English published.

A preliminary search was conducted searching on Scopus for the keywords "Scheduling" AND "Artificial Intelligence" in titles, abstracts, and keywords. Scheduling problems managed using AI is an attractive topic for scientific debates in various fields with an increase in the number of publications, as shown in Figure 2

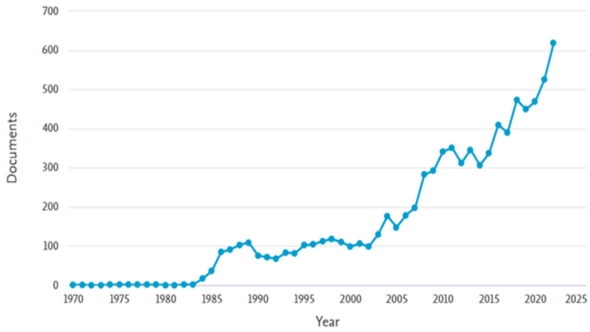

Figure 2. Number of publications during the years

The search for this analysis focused on how authors solve production scheduling problems using AI techniques limiting the analysis to articles published from 2011 (the year of the advent of I4.0) to 2022, and 4993 articles were found. A filter was used on the publication of the engineering domain only to exclude out-of-scope publications; this resulted in 1734 articles written in English. Then, a bibliometric analysis was conducted on these articles.

B. *Bibliometric Analysis*

One of the research questions wants to identify what are the most used AI techniques to solve scheduling problems and their purpose. To conduct a specific literature review, it is important to know the specific keywords to search for identify quickly useful papers in the database of Scopus. For this aim, it was used VOSviewer.

Thus, it has been possible to find common correlations among several keywords. In particular, only keywords capable of leading to AI techniques were selected. A minimum threshold of keyword occurrences of 10 has been set to exclude less frequent keywords.

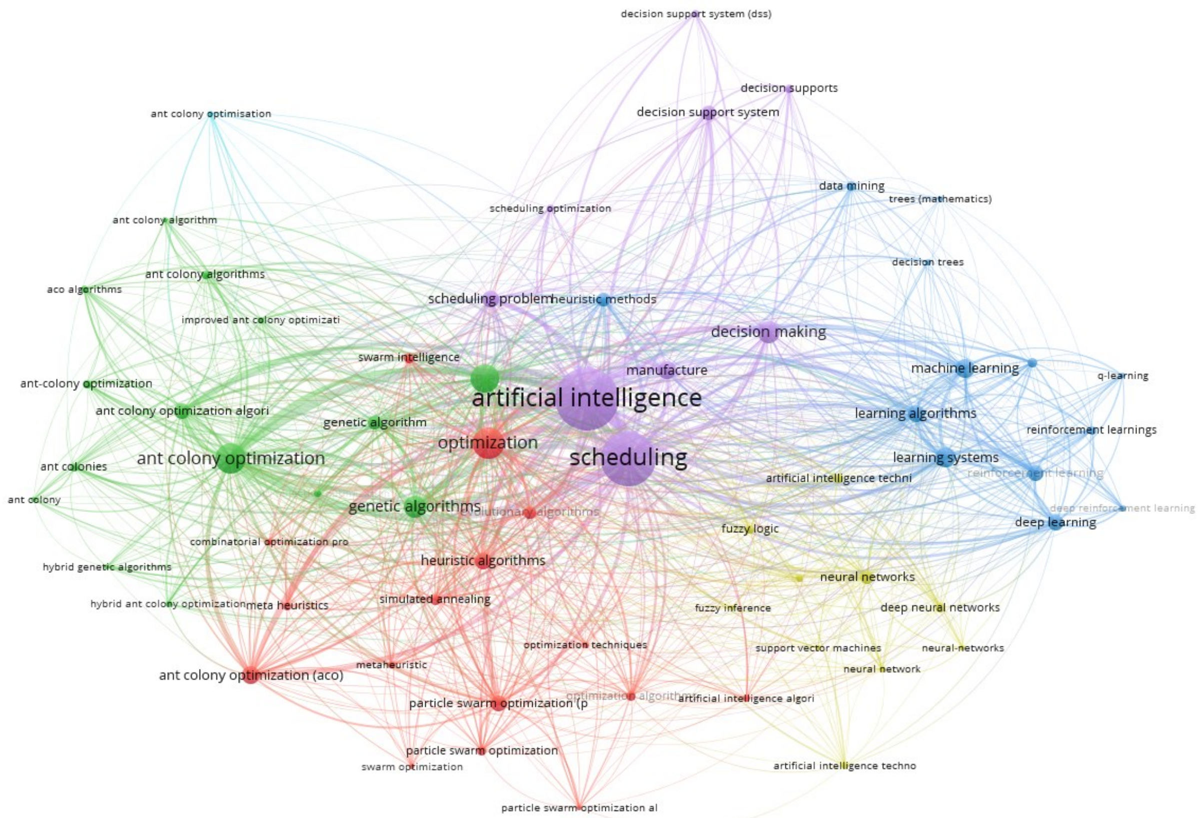

Figure 3 Tracking keyword through the use of VOSviewer

In Figure 3 is possible see the main AI techniques used to solve scheduling problems like, for example, Neural Networks (NN), Deep Neural Networks (DNN), Reinforcement Learning (RL), Swarm Intelligence (SI), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Fuzzy Logic (FL), Decision Trees (DT).

C. *Specific search*

From the results of bibliometric analysis, a more specific search on Scopus was conducted searching scheduling and AI techniques in order to see the number of publications.

Figure 4 shows the number of publications for each couple of keywords searched to see what AI techniques the most are widespread. This research shows that the most numerous contributions in the literature concern the use of PSO and NN for solving scheduling problems. The next stage of the research is to analyse how the authors solve industrial scheduling problems in real case studies through the use of PSO and/or NN algorithms.

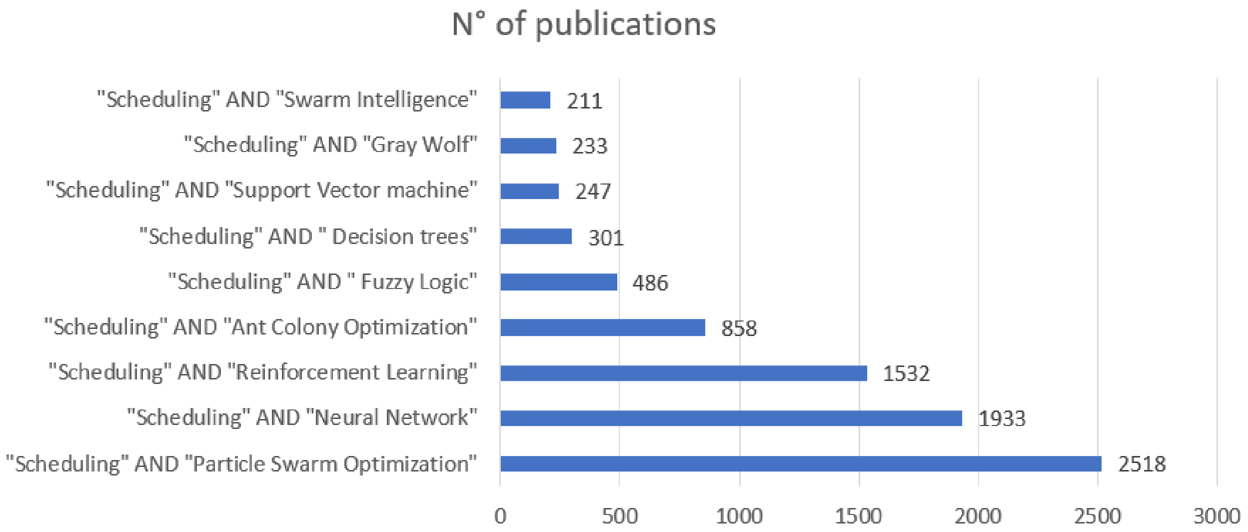

Figure 4:Number of publications with different combination of keywords

For this reason, a double search on Scopus database was conduct searching in title, abstract and keywords:

- "Scheduling" AND "Particle Swarm Optimization" AND "case study"
- "Scheduling" AND "Neural Network" AND "case study".

This choice was made because the aim of this analysis is to analyse which benefits and advantages companies have obtained from such algorithms, thus excluding all articles that illustrate an algorithm without application cases.

Only articles and conference papers written in English and published from 2011 to 2022 in the engineering domain were considered. A total of 181 publications were found for the first search, and 116 for the second. From these articles, reading titles and abstracts, out-of-context publications, and paid publications were excluded. A total of 15 articles were found that applied NN or PSO to solve scheduling problems in industrial case studies.

III. LITERATURE REVIEW OF RELEVANT PAPERS

This section reports on contributions by other authors to solve the scheduling problem within production sites using PSO and NN. This research focuses on understanding how the authors used these techniques and what benefits they brought to the companies.

A. *Particle Swarm Optimization*

To solve a particular scheduling problem, [6] realize a two-step method to optimize energy consumption in a Flexible Job-Shop (FJS) system. The first step consists of the implementation of a Genetic Algorithm able to optimize the machine tool selection for the production process. The second step is a combination of PSO and GA to optimize operations sequencing where the genetic operation of GA is used to increase the capacity of global exploration avoiding premature convergence of PSO. The proposed algorithm was tested in a case study and achieved a reduction in production costs of 8.5% and energy consumption of 10.2% compared to the previous scheduling programs used by the company where the framework was tested. A different hybrid approach was developed by [7] who realize an algorithm combining variable neighborhood search and PSO to solve parallel machine problems in the solar cell industry. This type of problem is called a Hybrid flow shop scheduling problem and comprises two general issues: parallel machines scheduling and flow shop scheduling. In the proposed case study, variable neighborhood search is used to decide in which order tasks are to be performed and PSO is used to decide the assignment of machines for all production orders. The proposed solution is better than the traditional PSO and the heuristic algorithm used by the company under investigation and achieves the solution of the scheduling problem in 43.16 seconds, faster than the other two solutions. [8] propose a combination of PSO with artificial immune to solve an assembly job shop scheduling problem in order to minimize the completion time. The algorithm was tested in a real case study and proved to find an optimal solution to the problem in only 106 seconds. [9] design two algorithms to solve the scheduling problem in the bakery industry: the first one use PSO meanwhile the second use Ant Colony Optimization (ACO) algorithm. A comparison of the two algorithms was conducted and shows that PSO is faster (39s when optimising makespan and 15s when optimising total machine idle time in the average calculation time) than ACO and returns better results in both optimisation problems. A re-entrant two-stage flow shop problem where all jobs must visit two times the sequence of the production process was solved by [10] using farness PSO (FPSO). FPSO differs from traditional PSO in that swarm behaviour learns from experience and improves the solution from the self-owned and distant population. The method was tested in a real case and the results were compared with results from traditional PSO and ACO. FPSO outperforms both approaches providing an average improvement in effectiveness of 39.47% and 42.99% compared to PSO and ACO for small-scale problems. [11] design a PSO algorithm to solve lot-size and scheduling problem in a tile industry. The problem is a classic four-stage flexible flow-shop environment, and the objective function was to find the minimum cost of production, inventory, and external acquisition. The proposed algorithm gave a scheduling program and lot-size in 479 s. A production schedule and maintenance which consider energy cost, machine production efficiency, and production target are developed by [12]. The PSO model presented was tested in one company and involves the implementation of joint energy and maintenance management. The implementation generated a reduction in production costs compared to the previously used approach. A different use of PSO is given by [13] who proposes a combination of PSO and ε-constraint method, a multi-objective decision-making method. It is considered a 'make-to-order' production system, responsible for the production and transportation of customer orders, the described problem is a combination of a flexible job-shop scheduling problem and a vehicle routing problem. The proposed scheduling algorithm is a bi-objective mixed integer model that can find a solution that minimizes production and transport costs and the weighted sum of delivery earliness and tardiness. A bi-objective algorithm to solve FJSP with uncertain processing times was developed by [14] too. They realize a combination of GA and binary PSO in order to minimize the makespan and a value of deviation about the expected makespan. The proposed method was tested in 9 case studies and performed better in terms of robustness than the stochastic method and a conventional method such as the hybrid GA. [15] realize a bi-objective scheduling optimization method for a single machine that minimizes energy consumption and total tardiness through the use of PSO. The algorithm was tested on a CNC machine and returns multiple solutions which different values of energy consumption or tardiness that support the process planner his choice.

B. Neural Network

An artificial NN algorithm to track the energy consumption of CNC machines was developed by [16]. The proposed algorithm is combined with a multi-objective optimisation model for the production re-scheduling process that minimises energy consumption, makespan and balanced machine utilisation levels. The proposed algorithm was validated on several industrial trials and achieved a 30% improvement in energy consumption and a 50% improvement in productivity. Another interesting approach to the scheduling problem was realized by [17]. In this case, there is a smart factory with 4 equal workstations, every single station has its own schedule program that runs on a distributed computer and realizes the scheduling with a metaheuristic method and has its own neural network algorithm (NN) that learns from the workstations. The learned knowledge was shared with a centralized computer system where there is a scheduling system based on multi-agent RL (MARL) logic (DQN method) that learns from the 4 workstations and shares this knowledge with the 4 workstations. The proposed solution reduces 11.9% the lead time compared with only DQN.

[18] develop a framework that combines commercial software tools for scheduling with a machine learning approach to predict machine failure in scheduling programs. The proposed approach was tested in a pharmaceutical company and different AI techniques were tested; the results show that the best performance was given by the use of the Decision Forest algorithm, but the NN algorithm gave better results in predicting the machine failure time.

A model that uses artificial NN to schedule the workforce of a company was designed by [19]. The aim of their algorithm was to predict the number of employees for the following days based on various factors such as customer requests number of working hours, etc. Thanks to this contribution, the waiting time of the company's employees was reduced to 2.3 minutes, leading to an increase in the company's productivity and a higher degree of customer satisfaction.

[20] use ANN to optimize the milling process parameters (energy consumption and surface roughness) for producing one single part. Based on the optimized parameters, several intelligent methods, such as Pattern Search, GA and Simulated Annealing are applied to find an optimal sequencing, setting-up and scheduling for multiple machines. In the case study, the Simulated Annealing algorithm was used in two forms. The first model aims to optimise energy consumption and makespan, while the second only optimises energy consumption. With the second approach, there is a reduction in energy consumption of 2795 kJ but an increase in makespan of about 23 min compared to the first.

IV. Discussion, future developments and conclusions

A. Discussion

From the precious contribution of authors was possible study how they approach to real cases production scheduling problem through the use of AI. The use of PSO or NN made it possible to solve a number of very different scheduling problems. In particular, PSO is extremely well suited to the realisation of both single-objective and multi-objective scheduling algorithms in a job shop, flow shop and other systems due to its flexibility in the programming phase. The use of NN also brought benefits in the various case studies reported in the literature. Unlike PSO, the application of NN algorithms often does not lend themselves to sequencing alone but is used to find correlations, parameters or other features that will be used to realise more accurate scheduling. One common aspect between PSO and NN is certainly that they have a high degree of flexibility, in fact, they apply in very different cases. Another common aspect is that they both lend themselves well to collaborating with other algorithms to create hybrid algorithms that increase the overall performance of the solution. Thanks to this study, it is possible to understand the wide use of these two AI techniques in solving production scheduling problems. The benefits they brought to companies are of different types such as calculation time, energy consumption, makespan, resource utilisation and allocation, etc., depending on what was to be optimised.

B. Future developments and Conclusions

The following article was written with the idea of clarifying two objectives:

- Understand what the tendency is to solve scheduling problems through the use of AI and what AI techniques are most widely used in the literature
- Analyse how other authors solve production scheduling problems in real cases and see what advantages they have achieved.

Thanks to bibliometric analysis, it was possible to answer the first question and see that the trend of using AI to solve scheduling problems in engineering is growing year after year, with the use of PSO and/or NN being the most widely used approaches in the literature. From this point, a more specific literature review was conducted to see how the authors solve production scheduling problems in real cases through the use of PSO and NN. Both AI techniques present different contributions in which the algorithms are used to solve different types of scheduling problems, classic NP-hard problems, like single-objective or multi-objective in several scenarios like job-shop, flow-shop, and not only. This study showed how, through the use of AI, the companies concerned obtained benefits that can be of different types depending on internal problems.

Future steps will concern the realisation of an algorithm for the optimisation of production scheduling for the pilots of the European AIDEAS project in order to enrich the contribution in the literature.

Acknowledgments

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