



Production Programming In The Manufacturing Industry

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Abstract

This research studies the Flow shop - Job shop methodologies, which play a fundamental role in the reduction of costs in factories when planning the production sequence. The selection methodology of articles used in this research took into account that the papers were indexed or approved, in addition to being in a range of no more than ten years of publication. The research results showed a higher percentage of articles on the job shop methodology. We concluded that minimizing production costs is the main objective of production scheduling based on Flow shop - Job shop methodologies. However, in the last decade, the objective has been focused on reducing energy costs since they allow to evaluate the processes to program when to turn on or off a machine.

Keywords: Production programming, scheduling, flow shop, job shop, sequencing.

1. Introduction

Production scheduling is a methodology that allows companies to project the operations necessary to meet the production demand in the short term. This allows to increase the company's efficiency and reduce costs by having the capacity that a company has to meet the demand in the shortest possible time, having the least amount of inputs and/or labor without reducing the service indicator.[1] There are different methodologies for scheduling operations. However, this article focuses on the most used methods in the last decade to minimize the environmental impact, such as Flow shop and Job shop.[2] The Job Shop method is based on the production schedule by order, this methodology collects data from the production data of the company, which is based on the production scheduling by order, this methodology is based on the production scheduling by demand, this methodology is based on the production scheduling by order.

The Job Shop method is based on the production schedule by order. This methodology collects data

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on a company's demand and simulates the production process order according to the delivery dates required by different customers. It is a way to optimize the development of production, programming the bottleneck of the process initially so that the service indicator is as expected, meeting the delivery dates that were agreed upon with customers upon receipt of orders. The simulation is carried out virtually and if the time is optimized to the minimum, the result is applied to the process physically. Verifying that the simulation was correct[3].

The Flow Shop method is based on production scheduling by large production flows, this methodology collects data on the production capacity of the factory according to the number of machines that the company has. It is a model that allows optimizing production by scheduling according to the company's machines, taking into account this, the Flow Shop method schedules production starting with the machines or processes that generate bottleneck, then schedules the other machines and finally simulates what would be the process of the product maximizing production, according to this the calculated transmission time cannot be greater than the actual time spent by the process.[4] To choose the method to use in the scheduling, the type of company, the machines' capacity and demand must be taken into account. When the demand is regular, the capacity of the machines must be taken into account and the Flow Shop method must be used for scheduling; on the contrary, when the demand is irregular, the Job Shop method must be used for scheduling, taking into account the capacity of the machines, but additionally the delivery dates of the orders.[5] This article reviews and compares two scheduling methods.

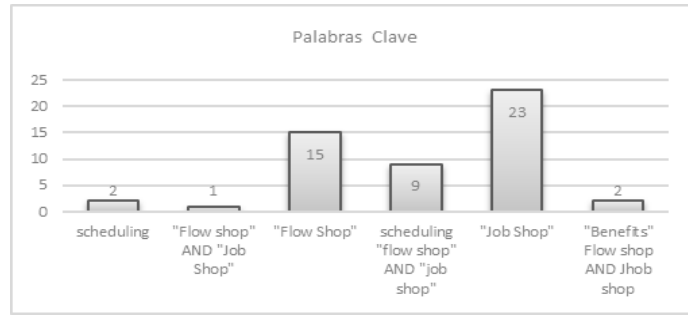
This article reviews and compares two specific methods, Flow Shop and Job Shop, based on research articles that present case studies of both methodologies, demonstrating how each method is used and under what circumstances they should be used for production scheduling.

2. Method

As a search strategy, publications were selected that met the following criteria: 1) those involving Flow shop and Jobs shop production scheduling methodologies and systems; 2) those mentioning Flow shop - Job shop scheduling success stories; 3) those including the benefits of scheduling with the production scheduling methods proposed.

The search for research articles was performed in different databases such as Science Direct, Google Scholar and Scielo, digital books were obtained from a digital library provided by a teacher specialized in the area of production scheduling. Papers that did not evidence the relevant methodologies of this article and articles published in journals that are not indexed were excluded. Initially, the components of the question were defined according to the brainstorming strategy, which were captured in a mind map. According to the above, the components of the question were represented, with which the following search equations were constructed, "scheduling", "Flow Shop", scheduling "flow shop" AND "job shop", "Job Shop" and "Benefits" Flow shop AND Job shop, the Boolean operators quotation marks were used with a percentage of 52% and AND with a percentage of use of 12%. Figure 1 shows the number of items found and used in this paper with the search equations.

Figure 1. Search equations



Further publications were identified from the reference list of the selected papers. The selection was made by reviewing the manuscripts' titles, abstracts and conclusions. Finally, 52 papers were selected, of which 98% are research articles and were provided by the Science Direct database and literature books in 2%. 34.62% were published between 2013 and 2018, 36.54% were published between 2019 and 2020 and 25% were published after 2021. (see Figure 2)

Figure 2. Articles by year of publication

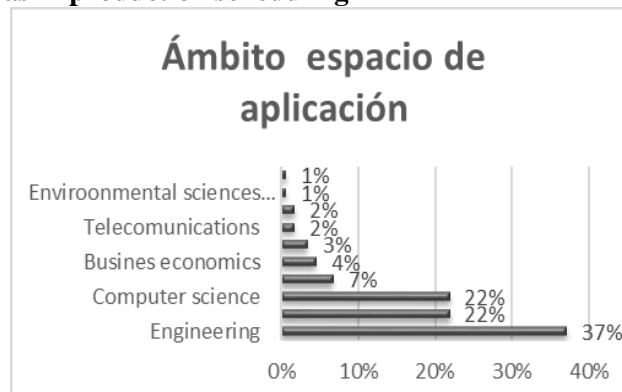


Most of the articles chosen for this document were published in Europe (47%) and Asia (49%), however, a minority (4%) of these were published in LATAM, specifically Brazil.

3. Results

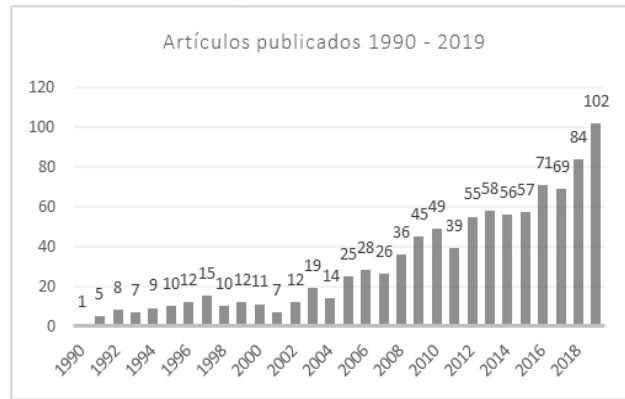
In the scheduling environment, developments are paramount to success. Initiated in 1990 by Schlie and Brucker, the difficulties of manageable shop floor scheduling attract researchers and practitioners in the modern decade. This group of inquiries could effectively address the industry's high flexibility scheduling drawbacks. Figure 3 shows the data of the areas with the most research in the production area [6].

Figure 3. Research areas in production scheduling



Different modeling possibilities and problem-solving procedures have been perfected in recent years within the production framework. There is an expectation that this trend will evolve in the future, because the number of publications is growing exponentially, considering the benefits it proposes for the industry in today's economic environment, as shown in Figure 4 [7].

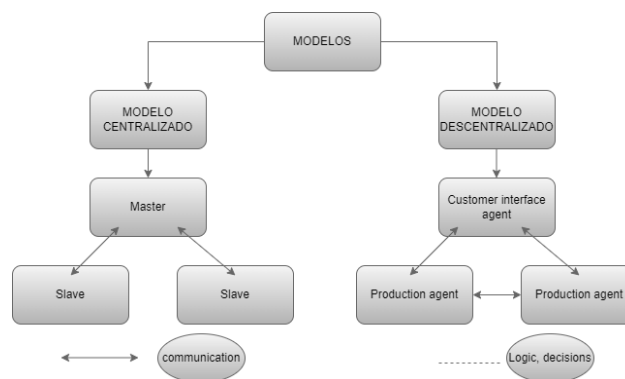
Figure 4. Published articles on production schedules between 1990 and 2019.



Technological results show that the staged decomposition strategy achieves optimal solutions four times faster than the integrated orientation with much less effort.[8] There is a need for more evolved, mathematically based planning and scheduling tools for production systems with complicated flows that remain subject to constant change. To apply such tools, it is imperative to improve data acquisition starting from the operational level on the shop floor. An information infrastructure has been postulated to enable this new type of scheduling to achieve significant optimization and improve productivity.[9] Metaheuristics has the advantage of the metaheuristic and can optimize the production process.

Metaheuristics have the potential to solve complex problems but require formidable computational power. The use of similar high-performance architectures in cloud computing and edge systematization supports the evolution of better metaheuristics, evolving with Industry 4.0 and solution methods to cope with their scheduling difficulty.[10] Centralized scheduling could achieve global performance optimization (including with high value), decentralized scheduling decisions in the multi-agent technique are more flexible and agents are more robust. and implementation), to address any disruptions that may develop on the shop floor. In parallel with a centralized architecture, development and testing is the more complicated way, as it requires the availability of physical units. Figure 5 shows how these programming models work.[11] Figure 5.

Figure 5. Centralized and Decentralized Programming Models



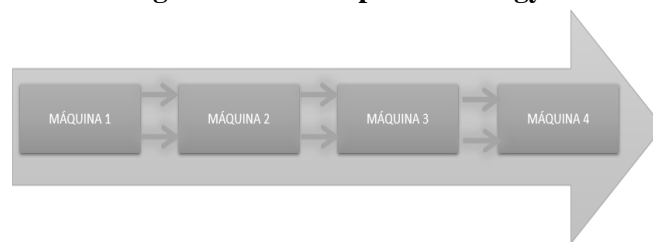
In industry, embedded improvement is often not feasible because elementary and complete information cannot be exchanged between systems. Constantly, industrial plants optimize the performance of production and utility systems sequentially with neither feedback, leading to suboptimal management. [12] The attendance training procedure outperforms naive MILP approaches and is competitive with a decreasing horizon MILP approach in terms of productivity, inventory levels, and customer service. The speed and flexibility of the reinforcement learning system are promising for real-time improvement of a scheduling system; however, there are causes to look for the adherence of data-driven deep reinforcement learning procedures and model-based mathematical improvement approaches.[13]

Accordingly, there are two methodologies for production scheduling based on time and cost optimization: Flow Shop and Job Shop.

3.1 Flow shop

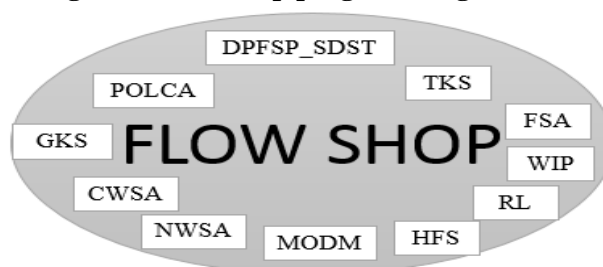
Flow shop scheduling is a composite optimization methodology, well known to arise in different production systems in which work tasks are planned by sequences, as seen in Figure 6. Although, there are different types of algorithms for scheduling in this methodology, the genetic algorithm aims to minimize the sum of processing and maintenance costs [14].

Figure 6. Flow shop methodology



The system's usefulness is measured by reducing the total flow and construction time. Due to the problem's difficulty, the product families are decided in the functionality of the operations time to maximize the execution in each of the cells with the use of a Genetic Algorithm. The flow store scheduling is performed on each family of parts formed to decide the succession of products for each set of cells by the utilization of multi-objective mixed complete linear programming. Both purposes are to reduce the total flow time and makespan to create a non-dominant solution.[15] The optimization objective is to reduce the cycle time. Some models are proposed according to the methods that exist for scheduling by this methodology, as seen in Figure 7, and some particular specifications of the problem are introduced, which allows finding the period time for each given solution quickly.[16] The optimization is based on the following methods.

Figure 7. Flow shop programming methods



This objective can be achieved at different levels: machine, product and system. levels: machine, product and system. At the system level, processors can minimise their system's energy consumption by using existing choice models and improvement techniques for production planning and scheduling.[17] In order to develop a production strategy, the decision-maker only has to choose the job scheduling planning and production scheduling.

To develop a production strategy, the decision maker, only has to choose the job scheduling planning, and does not need to consider the specific capabilities and competencies of the workers. However, in several practical construction systems workers are usually heterogeneous (i.e. supernumerary) (i.e. multi-skilled), they typically have different skills or have different acquired competences, this difference is primarily manifested in their trade efficiency, which significantly impairs the production schedule of the jobs. Therefore, multi-skilled workers should be considered once the problem of hybrid flow shop scheduling is studied.[18] The difficulty of flow shop scheduling is similar to that of multi-skilled workers.[18] The difficulty of hybrid flow shop scheduling is similar to that of multi-skilled workers.

The difficulty of Flow shop scheduling shares succession-dependent setup times (DPFSP_SDST) is a generality of the change flow shop scheduling problem with process-dependent setup times (PFSP_SDST), where there exists a group of identical factories in a PFSP_SDST composition. We discuss first allocating the jobs to the factories and then scheduling the jobs in each factory. [19] The flow shop industrial scheduling system allows to schedule two machines without intermediate buffers, so the deadlock situation can be eliminated. In addition, batches of different sizes are possible.[20] The implementation of a production line is detrimental to the production process.

Implementing a production line impairs the manufacturing cost, which concerns the processing time, and the work-in-process (WIP) inventories in a production line affect the maintenance cost, concerning the flow time. There is a trade-off between 2 purposes, to reduce the flow time and the manufacturing time. If the balancing drawbacks are not checked in flow shop scheduling, WIP inventories will be high in manufacturing, generating unnecessary maintenance costs.[21] The hybrid particle agglomeration optimization algorithm helps the scheduler decide the job execution sequence concerning consumer orders and develop efficient scheduling procedures to reduce the total flow time with low technical effort [22].

In the Flow shop methodology, there are several production control techniques TKS, GKS and POLCA. The most widely used method in make-to-order manufacturing is TKS because simulation studies show that it outperforms POLCA; although it has lower benefits than GKS, studies show tribute in aligning production control theory to industrial practice.[23] Production scheduling problems must be solved with execution times that support near real-time decision-making. Most real industrial Hybrid Flow Shop (HFS) production control problems must be solved to mitigate multi-objective values that create manufacturing drawbacks [24]. The requirements, such as resources and resources, can be met through a production scheduler.

Schedule sorting and integer scheduling are performed to meet the requirements, such as alternative resources, delivery dates and sequence-dependent processing times. Due to the combinatorial complexity, constraint scheduling approaches are proposed, which solve real-world cases up to optimization in a few seconds of runtime. The advantages of flow shop scheduling are shown in Figure 8 [25].

Figure 8. Advantages of the Flow shop methodology



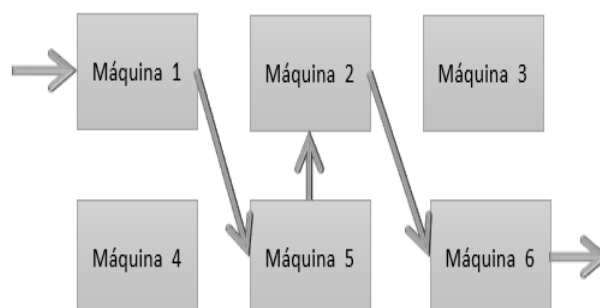
Flow-shop scheduling (FSP) using reinforcement learning (RL), which approximates the value function with a neural network (NN). Under the strategy, the action, state, reward signal and value function of the FSP are presented in detail in the scheduling, taking into account the intrinsic characteristics of the FSP, the information is displayed in RL states, including the maximum, minimum and average of the waiting time and remaining operations, as well as the load of the machines. The optimization scheduling policies correspond to the specific states and have been converted into RL actions. According to the above, the NN establishes the correspondence between the states and the actions, and thus select the action with the highest probability under a specific state [26].

The objectives of Flow shop scheduling are the minimum duration (C_{max}) as well as the maximum duration of jobs (T_{max}). This difficulty is known as NP-hard. There are three simulation-based bi-objective optimization methods, CWSA (classical weighted simulated annealing), NWSA (normalized weighted simulated annealing), and FSA (fuzzy simulated annealing), are performed for solving problems to find approximations to Pareto optimization. Because meta-heuristic algorithms are very vigilant of parameter values, a new reliable method called Taguchi which has multi-objective decision-making (MODM) as its orientation is considered, these algorithms are tested by solving small and large-scale problems.[27]

3.2 Job Shop

In Job shop scheduling, machines are assigned to sets of operations optimally, as seen in Figure 9. The objective is to improve optimization based on biogeography to reduce waiting time.[28] Flexible job shop scheduling (FJSP) has enormous feasibility in reducing energy consumption in the manufacturing system due to flexibility in machine selection, job succession, and decision-making on turning on and off idle machines.[29] The FJSP is a flexible scheduling system.

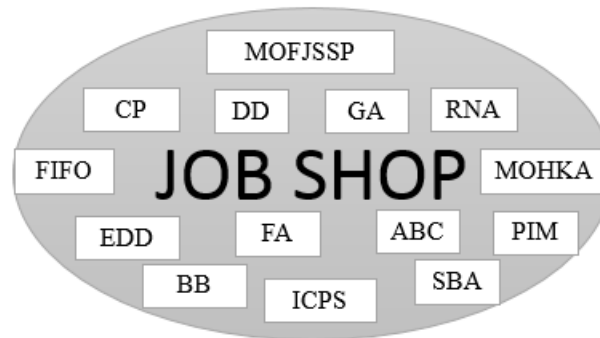
Figure 9. Job shop methodology



The important model is based on a single resource (e.g., a single machine) and a group of construction jobs, each characterized by a cost and a probabilistic win share. A failure causes the failed job to be reworked or the whole process to restart from the first job.[30] There are different models in terms of

scheduling as seen in Figure 10, complete mixed (PIM) and constraint scheduling (CP) are some of these methods. We use the features of positional sets and disjunctive graphs to build efficiently tight MIP formulations. Moreover, the features are recovered by polyhedral constructions of the linear ordering and defined in a disjunctive graph to facilitate the CP model formulation and minimize the number of dominant shifters.[31] In addition, the features are recovered by the polyhedral constructions of the linear ordering and defined in a disjunctive graph to facilitate the formulation of the CP model and minimize the number of dominant shifters [31].

Figure 10. Job shop scheduling methods



A production process is considered in which jobs are transported to assigned stations by two collaborative robots. A learning and simulation domain is performed to evaluate the feasibility of the obtained scheduling. The results are compared with a First In, First Out heuristic. The primary purpose is to consider robot displacement and collision avoidance without wasting unnecessary time. Then arbitrary instances of the scheduling problem are solved. The presented procedure leads to feasible schedules.[32] The first-in, first-out (FIFO) heuristic is combined with the earliest delivery date (EDD) heuristic and on-site experience of real production lines. In functionality of constraining conditions such as available processing apparatus sets accessible processing apparatus groups, hierarchical collaborations between elements, mold due date designated in the mold building project. [33].

Process mining techniques to examine the resolutions, the initiative is to understand the solutions generated by gene algorithms as process executions, exemplifying the production of a part as a process instance executed on selected workstations.[34].

A genetic algorithm with a random key encoding has as its target functionality the weighted improvement that keeps in mind the production overhead and the waiting era that should be minimized. A particular encoding of the solution: the assignment of cobots to workstations, the assignment of jobs to different workstations and the priority of jobs. The results present to what extent the weighted target functionality can be reduced by deploying different collaborative robots in a real-world production line. Furthermore, the results coded with biased random keys are compared with the classical solution coded with completes. With biased random key coding, superior results were obtained than with standard integer coding [35].

The concept of zero-defect manufacturing mandates that any occurrence in production should have a counterpart to mitigate it. This approach creates the need for more frequent rescheduling of the shop floor to accommodate corrective activities.[36] After completing a job on one machine, it must be transported to the next machine, which takes some time. However, transport times are not usually taken into account in the literature.[37] The following is an example of this.

Customized production and customized services are common business models in globalized production and are one of the advantages of Job shop scheduling, which are shown in Figure 11. They have the potential to be discovered, for example, in the inquiry of materials using high-throughput systems and the overhaul of spare parts. In both cases, there are warehouses with different requirements and reduced capacity in the systems. The reactivity of such systems is important for an immediate attitude to consumer demands [38].

Figure 11. Advantages of the Job shop methodology



The engine of the BB (disjunctive network model) is the Giffler-Thompson active scheduling generation procedure. The performance of the procedure is highly dependent on the selection of the child nodes in the first branching phases. To aid the selection choice, some properties of the nodes are stored in the BB procedure, and the mixed linear programming model informs the ideal selection at each branching phase. The stored data of a test problem instance is analyzed by genetic programming (GP) to create rules for choosing the correct nodes.[39] The stored data of a test problem instance is analyzed by genetic programming (GP) to create rules for choosing the correct nodes.[39] The distributed job shop distributed programming problem is a distributed job shop problem.

The distributed job shop scheduling problem (DJSSP) is a generalization of the traditional job shop scheduling problem (JSSP), characterized by simultaneously assigning jobs to different factories/shops and deciding their processing succession. Since energy efficiency and productivity significantly affect organisations' benefits, 2 criteria (i.e., job duration and total energy consumption) are applied to evaluate the JSSP.[40] Job scheduling from an energy-saving view in a real company computer system. After a preliminary introduction on the concepts of sustainability and Industry 4.0, and how they remain connected, and a second part dealing with Smart Factory, capable factories aimed at customization and flexibility. [41].

Although the procedures, tools and engineering standards for industrial cyber-physical systems (ICPS) have matured and remain more defined, the challenges to apply them to the development of production systems towards ICPS remain difficult for practitioners and experts, and even more so for students. "Digitization and Virtualization of ICPSs" (DVoICPS) is an essential issue for different sets of students in computer science, electronics, mechanical engineering, and others.[42] The "Digitalization and Virtualization of ICPSs" (DVoICPS) is an important issue for different sets of students in computer science, electronics, mechanical engineering, and others.

The Multi-Objective Heuristic Kalman Algorithm (MOHKA) enhanced estimation procedure is used for solving Multi-Objective Flexible Programming (MOFJSSP) drawbacks. Next, MOHKA is applied to solve MOFJSSP with an improved real number coding system, optimized for three benchmark improvement frontiers, the largest era of completion of all jobs (makespan), the total workload on each of the machines, the critical machine workload (the maximum workload in the middle of the machines). [43]

Scheduling procedures are separated into two types: exact methods and approximate procedures. Static scheduling is based on teaching that all jobs to be processed remain in a condition to be processed. When the project schedule is recognized, then the project does not require further scheduling. In the actual production process, as the scope of the production operation continues to appear to possess alteration components, such as overtime processing or ahead, an emergency order to join, and inaccurate processing time estimates, and so on, it will make the project schedule obsolete. Therefore, according to changes in actual conditions, we must adjust the draft schedule repeatedly, which is called dynamic scheduling. Exact procedures build one or several models of improving the target functionality to obtain an optimal solution by transforming the production scheduling drawbacks into fairness or difference constraints. Most scheduling drawbacks are proven NP drawbacks. As the scheduling problem expands with the increase in the number of devices, its possible solution increases to an exponential order and exact procedures cannot obtain an optimal solution in a reasonable period easily, so exact procedures do not have the possibility to for solving practical drawbacks [44].

For the epoch-based model to obtain an optimal solution the time intervals have to be considered as small as possible, including each time unit should be equal to one second[45]. The effectiveness of the ANN-based DD allocation model evaluates its performance with other dynamic DD allocation rules: Total Dynamic Work Content, and Dynamic Processing. ANN-based DD allocation models are more effective than only accessible fixed DD allocation rules, as concluded by other researchers, in addition to the most effective dynamic DD allocation rules [46].

The job store scheduling problem is a well-known scheduling drawback in which most of them are sorted into deterministic nonpolynomial (NP) drawbacks because of their difficulty. genetic algorithm (GA), selective breeding algorithm (SBA), tabu averaging algorithm and ant colony algorithm are popularly known as metaheuristic algorithms, have proven to be the most efficient algorithms for solving various JSSP so far. [47]

The tools can be easily adjusted to different versions of idealization or scheduling drawbacks, overcoming the lack of flexibility mainly linked to procedures more adapted to the drawbacks proposed in the literature. The encoding used by the metaheuristic is an AND list of jobs. A metaheuristic based on a unique stochastic descent solution is used; therefore, the neighborhood system is a permutation of jobs. The algorithm estimates the jobs in the order of the list to schedule them and assign them to the requested resource, according to the various constraints. The objective functionality evaluates the solution. According to this evaluation, the solution is chosen or not by the metaheuristic. Finally, from the execution, the solution given by the hybridization is the best job list that optimizes the objective functionality by implementing the list algorithm. [48].

The Job Store Scheduling Problem (JSSP) belongs to the existing scheduling models in practice which is among the most difficult combinatorial improvement drawbacks. The ABC technique (Artificial The ABC technique (Artificial Bee Colony) relies on the fact that each of the particular artificial bees move in an averaging location and select food sources by correctly adapting their location, their technical knowledge and being fully aware of the settlers of their nest.[49] The ABC technique (Artificial Bee Colony) relies on the fact that each of the particular artificial bees move in an averaging location and selects food sources by correctly adapting their location, their technical knowledge and being fully aware of the settlers of their nest.[49].

Keeping in mind the time of use (TOU) and the staggered cost of electricity, a mathematical model of the groups is established to minimize the expenses of energy consumption in production and the price of energy consumption in production and assembly. To solve the discontinuous domain problem that the standard Firefly Algorithm (FA) is not correct for shop floor energy-saving scheduling, for shop

floor energy saving, an improved firefly algorithm is used to solve the mathematical model. The encoding, decoding and localization update of the algorithm are redesigned. A 3-layer encoding composition based on workpiece succession, start epoch and change tactic is used; for the iterative process of encoding workpiece succession, Hamming distance instead of Euclidean distance is used to calculate the pose distance between firefly persons. [50]

3.3 Benefits

The genetic algorithm achieves good resolutions already after a few seconds up to certain min, which implies that this approach can be used for real-time choice making in a cyber-physical system in the era of Industry 4.0.[51] One of the approaches that these methodologies have besides reducing production costs is to minimize environmental impact by reducing energy consumption as seen in Figure 12.

One of the approaches that these methodologies have, in addition to reducing production costs, is to minimize the environmental impact by reducing energy consumption, as seen in Figure 12.



Digitalization opens up countless opportunities for improving production. The potentials range from monitoring the status of personal machines to fully autonomously controlled production systems. However, investments are often needed to exploit those potentials. Organizations constantly need to connect machines, market, upgrade or expand IT systems or realize digital twin projects in various apartments. Implementing such projects requires a comprehensive study of the system and expertise in different technical and scientific disciplines. An additional economic evaluation needs further financial knowledge [52].

4. Conclusions

In the last three decades, the research of these methodologies has increased and therefore their application in different areas because the impact is not only in the production area, but also because they are methods that allow reducing manufacturing overhead costs.

Researchers are concerned about reducing energy costs by reducing consumption and creating a positive environmental impact. According to the literature, the Flow shop and Job shop methodologies are the best programming systems to reduce these costs. They evaluate the processes to program when to turn off or turn on a machine according to the number of orders.

Flow shop and Job shop methodologies optimize sequence production for each company, as they are methodologies that admit unique problems to propose unique solutions. On the other hand, scheduling

methods are usually proposed with algorithms because all companies are different and each problem is unique, therefore, not all processes can be planned in the same way, and the ideal is to propose a unique algorithm for each process to find the most optimal solution in each case.

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Appendix A. An example appendix

Authors including an appendix section should do so after References section. Multiple appendices should all have headings in the style used above. They will automatically be ordered A, B, C etc.

A.1. Example of a sub-heading within an appendix

There is also the option to include a subheading within the Appendix if you wish.

Makalenin Türkçe başlığı buraya yazılır....

Özet

Türkçe özet.

Anahtar sözcükler: anahtar sözcükler1; anahtar sözcükler2; anahtar sözcükler3

AUTHOR BIODATA

Insert here author biodata.