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Survey in solving the Flow Shop Scheduling with Cat Swarm Optimization and Genetic Algorithm

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Abstract. The paper investigates two metaheuristic algorithms for solving Flow Shop Scheduling. These two algorithms are the Cat Swarm Optimization and the Genetic Algorithm. Both algorithms are metaheuristic algorithms that maintain and improve a population of solutions during iterations. The Cat Swarm Optimization algorithm is inspired by the behavior of cats. The Genetic Algorithm is about reproduction. It includes operators such as crossover, mutation, and selection. In this article, the basic Flow Shop Scheduling task is presented, and then the two metaheuristic algorithms are also described in detail. Then, the search results of the Google Scholar and Elsevier publication databases are presented. After that, the most important articles and the tabular summary of them are presented.

Keywords: Flow Shop Scheduling, Cat Swarm Optimization, Genetic Algorithm

1. Introduction

This article aims to present and review the literature on a production scheduling problem, which is one of the best-known problems, the Flow Shop Scheduling [1] problem. It examines how jobs should be sequenced. The jobs run in the same order, on the same line. There are n jobs and m machines in the system. Each job is processed in the same order on each machine. A machine can only process one job at a time. A job can only be on one machine at a time. The Flow Shop problem well models practical tasks such as assembly line production, mass production, food or automotive production lines. The objective function is most often the makespan minimization, but it can also be the minimization of average lead time, the minimization of tardiness, or the maximization of machine utilization.
Cat Swarm Optimization [2] is a metaheuristic optimization algorithm based on swarm intelligence. It was inspired by the natural behavior of cats. Cats have two distinct activities in nature, namely seeking mode (calm observation, local search) and tracing mode (fast movement, global search). In the algorithm, a cat represents a possible solution. Each cat is either in seeking or tracing mode. The ratio of the two modes is determined by the mixture ratio (MR). Seeking Mode (local search) is responsible for exploitation. Several slightly modified solutions are created and the best one is selected. Tracing Mode (global search) serves as the exploration

phase. The cat moves towards the best solution found so far. The algorithm consists of the following schematic steps:
1. Generating initial population
2. Calculating fitness values
3. Cats are either in seeking or tracing mode (determined by MR value)
4. Executing seeking/racing mode
5. Updating best solution
6. Checking termination condition (iteration number, running time, convergence, etc.)

The Genetic Algorithm [3] is an evolutionary metaheuristic optimization method. It is based on natural selection and genetic inheritance. It uses selection, crossover and mutation operations to continuously improve the population. Common selections are roulette wheel selection, tournament selection, rank selection. During the crossover, two new individuals are created from two selected parents. Several crossover methods have been developed, the most common for permutation tasks are: PMX (Partially Mapped Crossover), OX (Order Crossover), CX (Cycle Crossover). A mutation is a random, small change on a given selected individual. There are several mutation techniques, for example, the most common for permutation representation are: swap, insert, inversion. The schematic steps of the algorithm are as follows:
1. Generating initial population
2. Calculating fitness values
3. Selection phase
4. Crossover phase
5. Mutation phase
6. Creating new population
7. Evaluating termination criteria (reach of iteration number, convergence, running time, etc.)

In the following, the article presents the searches using the databases for the two metaheuristic algorithms in the Flow Shop Scheduling solution.

2. Search results based on publication databases

This section presents the results of the searches performed on the publication database. The searches were performed in the Google Scholar and Elsevier databases for the Cat Swarm Optimization and Genetic Algorithm algorithms and the Flow Shop Scheduling task.

2.1. Google Scholar database

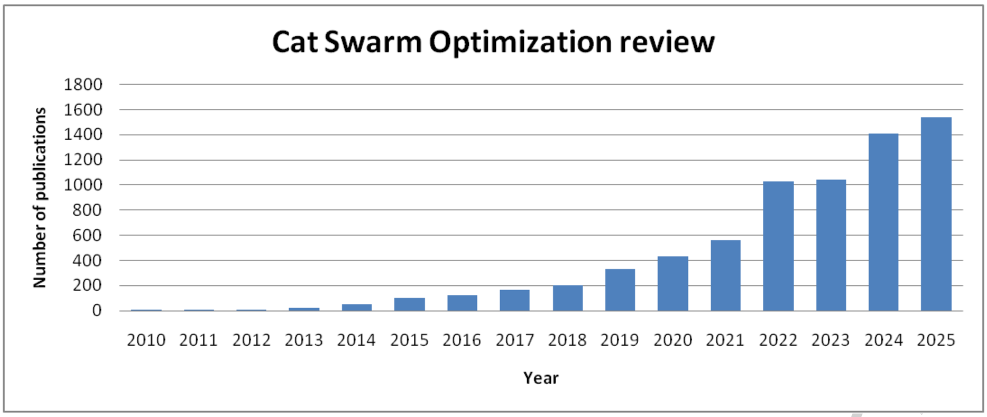

Figure 1. Google Scholar result: “Cat Swarm Optimization”and “review”

Figure 1. contains the results of the Google Scholar database, where the keywords were “Cat Swarm Optimization” and “review”. It shows the number of publications between 2010 and 2025. In 2010, 4 articles were published, in 2015, 103, in 2020, 431, and in 2025, 1540 articles were published by the researchers. As can be seen in the diagram, the number of articles has been increasing steadily over the years.

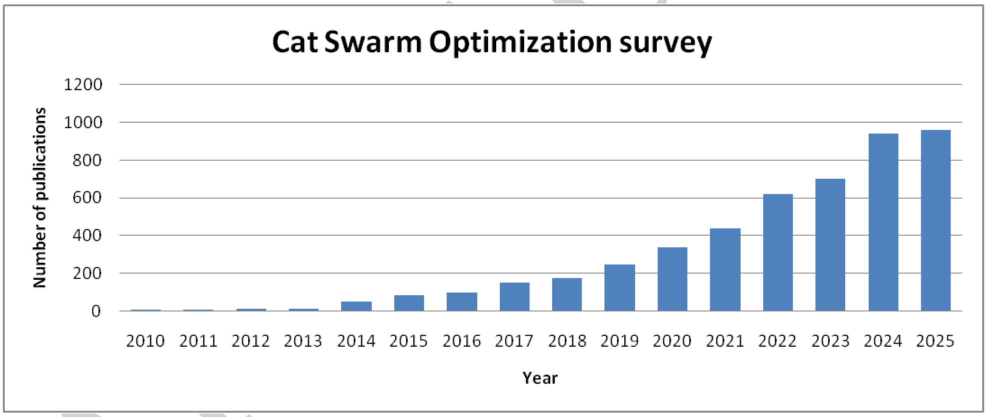

Figure 2. Google Scholar result: “Cat Swarm Optimization” and “survey”

The following searches are for Genetic Algorithm.

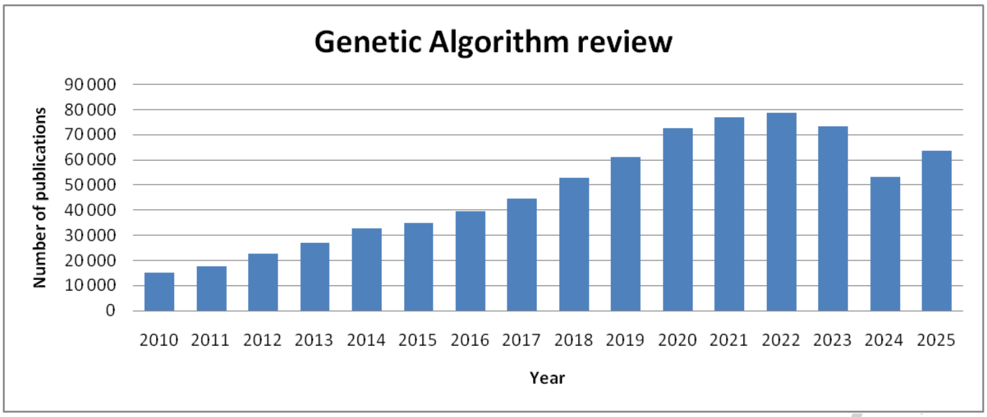

Figure 3. Google Scholar result:
"Genetic Algorithm" and "review"

Figure 3. presents the Google Scholar results for the Genetic Algorithm, where it shows the number of publications per year between 2010 and 2025. It can be seen that in 2010, 15,100 articles were published, in 2015 35,000, in 2020 72,500 and in 2025 63,600 articles were written by the researchers. Until 2022, the number of articles published per year increased continuously, and then from there there is a small decrease in the number of articles.

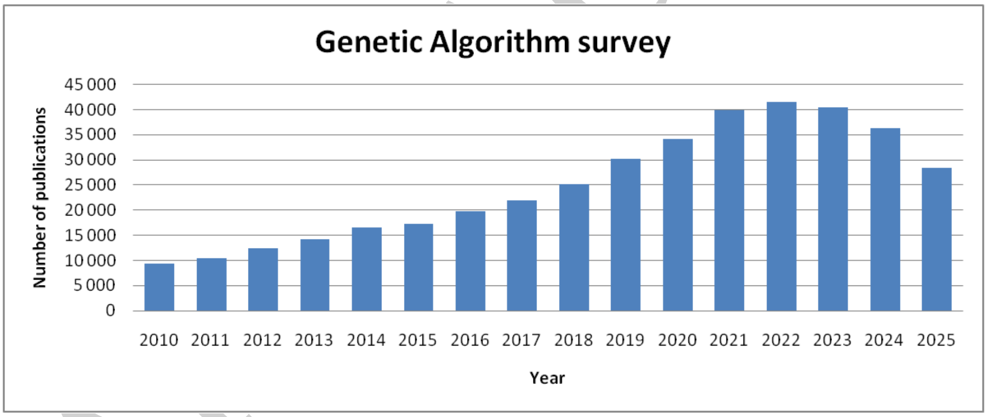

Figure 4. Google Scholar result:
"Genetic Algorithm" and "survey"

In terms of survey articles, Genetic Algorithm continuously increased until 2022, after which the number of articles showed a decreasing trend. In 2010, 9310 articles were published, in 2015 17300, in 2020 34100 and in 2025 28400 articles.

The following tables present the search results obtained for the Flow Shop task and combinations of metaheuristic algorithms (Cat Swarm Optimization and Genetic Algorithm).

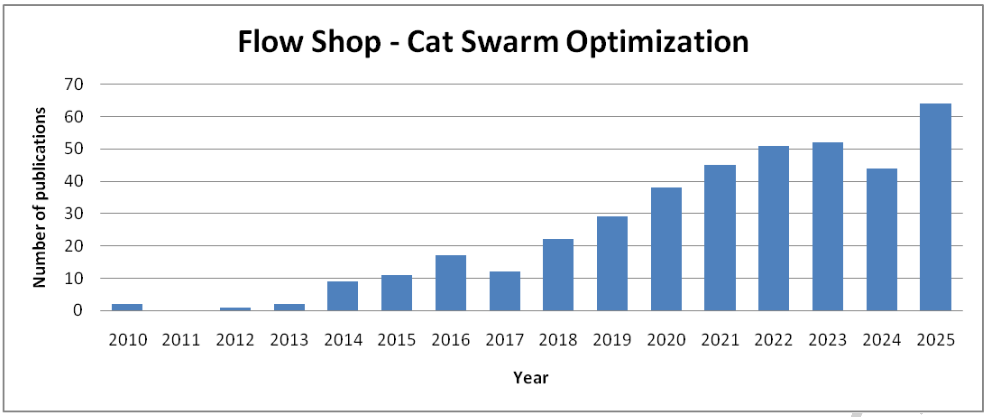

Figure 5. Google Scholar result:
"Flow Shop" and "Cat Swarm
Optimization"

Figure 5 shows the results for the combinations of "Flow Shop" and "Cat Swarm Optimization" between 2010 and 2025. In 2010, 2 articles were published on the topic, in 2015 there were 11, in 2020 there were 38, and in 2025 there were 64 such articles.

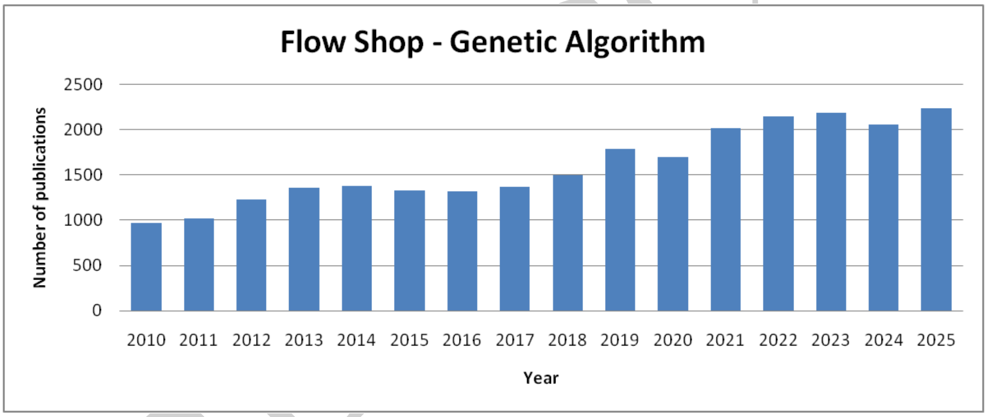

Figure 6. Google Scholar result:
"Flow Shop" and "Genetic Algorithm"

In the case of Figure 6, the Genetic Algorithm was the focus of the study. Here we find much higher publication numbers. 966 articles in 2010, 1330 in 2015, 1700 publications in 2020 and 2240 articles in 2025. So the number of published articles has increased steadily over the years.

2.2. Elsevier database

The following are the search results of the Elsevier database.

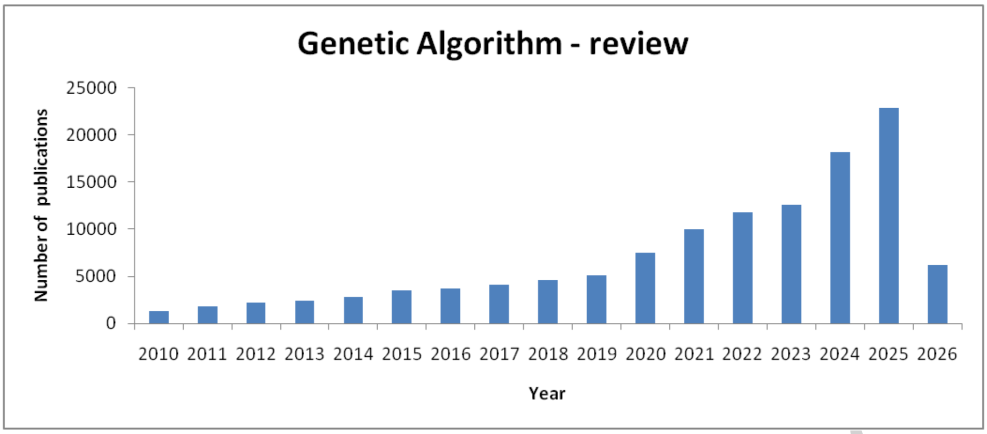

Figure 7. Elsevier result: "Genetic Algorithm" and "review"

Figure 7 shows the number of Genetic Algorithm review articles. It can be seen that the number of publications has been increasing continuously over the years. In 2010, 1344 articles were published, in 2015 3529, in 2020 7545 articles, while in 2025 22860 publications were published.

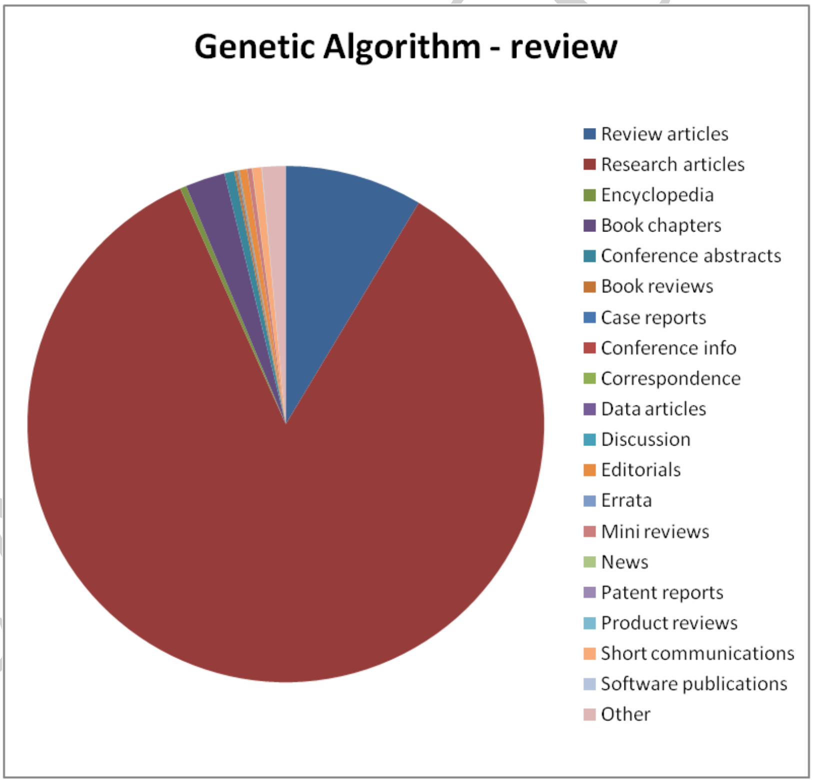

Figure 8. Elsevier result for article type: "Genetic Algorithm" and "review"

Figure 8 shows the article type, which shows that the second most common type is review articles (11,262 articles), while research articles are the most common (110,817 articles).

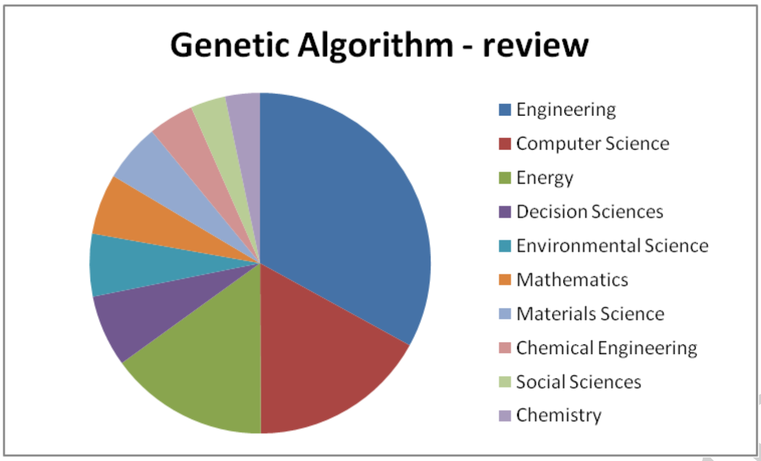

Figure 9. Elsevier result for subject areas: "Genetic Algorithm" and "review"

Figure 9 shows the subject areas for the search "Genetic Algorithm" and "review". It can be seen that the following topics are the most popular: engineering (59785 items), energy (27351 items), materials science (10003 items), mathematics (10420 items).

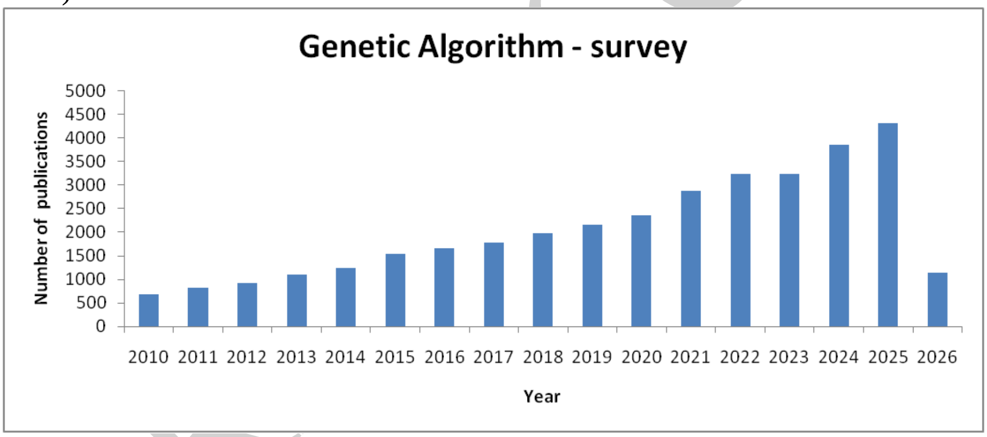

Figure 10. Elsevier result: "Genetic Algorithm" and "survey"

Figure 10 shows the Genetic Algorithm publications by survey keyword by year. It can be seen that the number of published articles has been increasing continuously over the years. In 2010, 683 articles were published, in 2015, 1546 articles, in 2020, 2366 articles, and in 2025, 4322 articles were published.

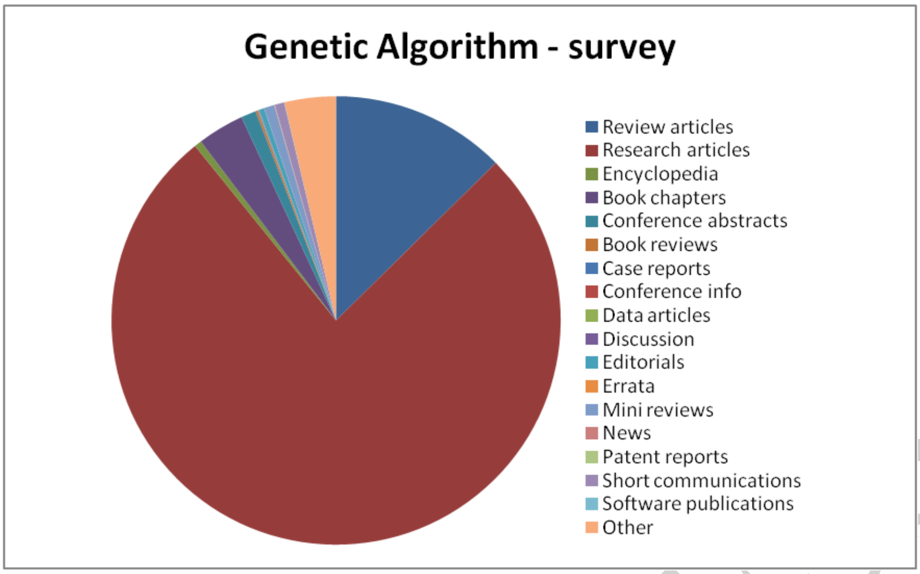

Figure 11. Elsevier result for article type: "Genetic Algorithm" and "survey"

The article type is shown in Figure 11. Research article type accounted for the most, 30,761 pieces.

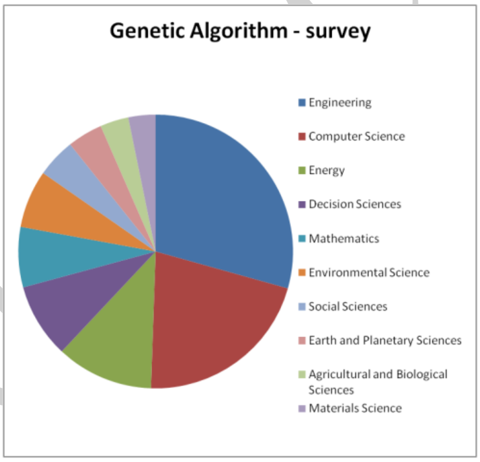

Figure 12. Elsevier result for subject areas: "Genetic Algorithm" and "survey"

Figure 12 shows the subject areas. The most articles were published in the Engineering (16,347) and Computer Science (11,805) subject areas.

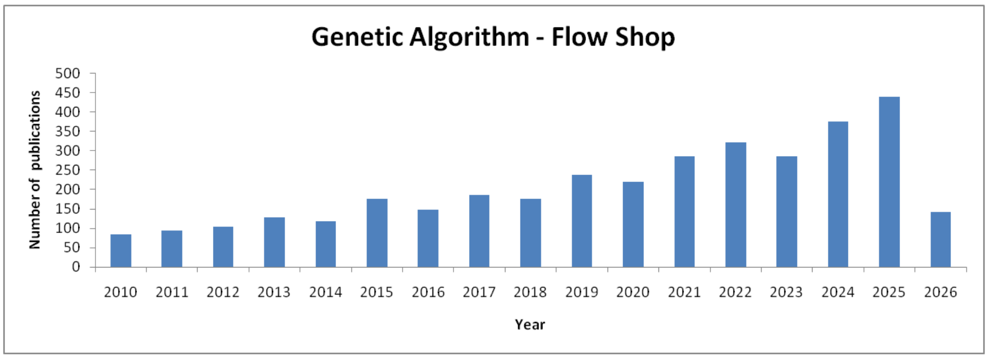

Figure 13. Elsevier result: "Genetic Algorithm" and "Flow Shop"

Figure 13 shows the results of the Genetic Algorithm for the Flow Shop task. It can be seen that the number of published articles has increased almost continuously over the years. In 2010, 85 articles were published, in 2015, 176 articles, in 2020, 219 articles, and in 2025, 440 publications were published.

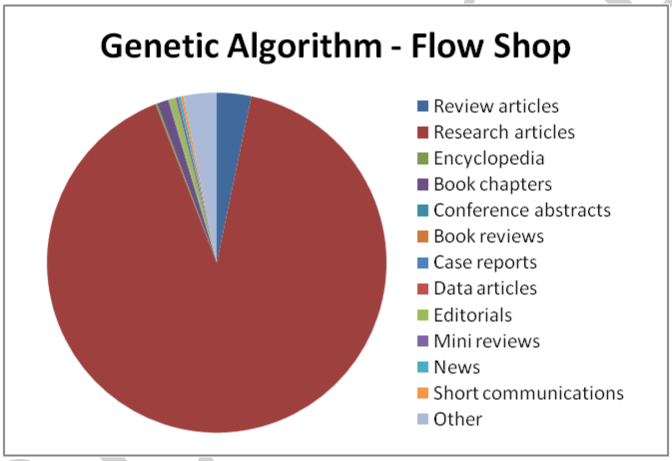

Figure 14. Elsevier result for article type: "Genetic Algorithm" and "Flow Shop"

Figure 14 shows the article type distribution for solving the Flow Shop problem with the Genetic Algorithm. It can be seen that most articles fall into the research article type.

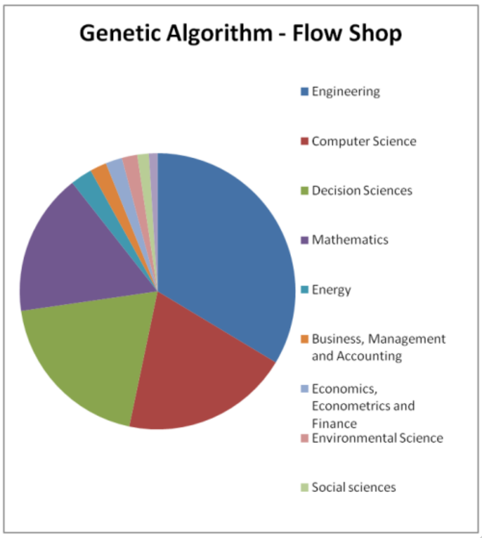

Figure 15. Elsevier result for subject areas: “Genetic Algorithm” and “Flow Shop”

Figure 15 shows the Elsevier results by subject area. The following subject area types were the most popular: engineering, computer science, decision sciences, mathematics.

3. Most important articles

This section presents the most important articles on the topics of Cat Swarm Optimization and Genetic Algorithm Flow Shop Scheduling.

3.1. Cat Swarm Optimization

In the article of [4], the Cat Swarm Optimization algorithm is used to solve Dynamic Task Scheduling. The authors developed a hybrid metaheuristic, because CSO is also used with the Simulated Annealing algorithm. The Orthogonal Taguchi Method is also used in the article. The sizes of the tasks were as follows during testing: 100, 200, 300, 400, 500, 600, 700, 800, 900, 1000.
In the article of [5], the authors presented a literature review, where they present Flow Shop Scheduling variants. These variants are the following: Permutation Flow Shop Problem (PFSP), Permutation No-Idle Flow Shop Problem, No-Wait Flow Shop Problem, Non-Permutation Flow Shop Problem (NPFS), Blocked Flow Shop Problem, Hybrid Flow Shop problem. In the following, the article also mentions metaheuristic and heuristic algorithms, such as the following algorithms: Simulated Annealing Algorithm, Genetic Algorithm, Tabu Search Algorithm, Ant-Colony Optimization Algorithm, Particle Swarm Optimization Algorithm, Cuckoo Search Algorithm, NEH Heuristic, Discrete Differential Evolution (DDE), Scatter Search, Largest-Order-Value, Differential Evolution (DE), Variable Neighborhood Search, Quantum Evolutionary Algorithm (QEA), Estimation Of Distribution Algorithm (EDA), Global-Best Harmony Search Algorithm, Discrete-African-Wilddog Algorithm, Firefly Algorithm, Ranked Order Value, Teaching–Learning-Based Optimization Algorithm, Largest Order Value (LOV) , Variable Neighborhood Search (VNS), Simulated Annealing (SA), Cat Swarm Optimization Algorithm (CSO), Backtracking Search Algorithm (BSA), Bat Algorithm,

Combined Decision Tree (DT) with Scatter Search (SS), Hybrid Monkey Search Algorithm (HMSA), Shortest Processing Time (SPT) and Longest Processing Time (LPT) Dispatching Rules, Hybrid Whale algorithm (HWA), Largest Ranked value (LRV), Crow Search Algorithm (CSA), Simulated Annealing (SA), Variable Neighborhood Search (VNS).

In the publication of [6], the Cat Swarm Optimization survey is presented. The following algorithm variations are reported in the article: Discrete Binary Cat Swarm Optimization Algorithm (BCSO), Multiobjective Cat Swarm Optimization (MOCSO), Parallel Cat Swarm Optimization (PCSO), CSO Clustering, Enhanced Parallel Cat Swarm Optimization (EPCSO), Average-Inertia Weighted CSO (AICSO), Adaptive Dynamic Cat Swarm Optimization (ADCSO), Enhanced Hybrid Cat Swarm Optimization (Enhanced HCSO), Improvement Structure of Cat Swarm Optimization (ICSO), Opposition-Based Learning-Improved CSO (OL-ICSO), Chaos Quantum-Behaved Cat Swarm Optimization (CQCSO), Improved Cat Swarm Optimization (ICSO), Hybrid CSO-GA-SA, etc. Several application possibilities are also presented, such as detecting communities in social networks, as a routing algorithm in wireless sensor networks (WSN), optimal power allocation in WSN, optimizing channel allocation in smart network communication, optimizing well placement in oil fields, etc.

In the article of [7], the authors present and solve a version of Flow Shop Scheduling where sustainability also plays a significant role. In the Hybrid Flow Shop Scheduling Problem (HFSP), different products, heterogeneous machinery and labor are available. This problem is discussed in the article.

In the article of [8], the authors present the Permutation Flow Shop Scheduling task. The task was solved using the Cat Swarm Optimization algorithm. The algorithm also compares its test results with several other algorithms, such as the Improved Cat Swarm Algorithm, Cat Swarm Algorithm, Particle Swarm Algorithm, Bat Algorithm. The efficiency of the algorithms was tested on the Car dataset (Car 1-Car7).

In the publication of [9], the authors solve the Open Shop Scheduling task using Cat Swarm Optimization. The efficiency of the algorithm is also tested on the Taillard dataset. The test runs from small test benchmark data to large data. In most cases, the results of the algorithm reached or were very close to the best known values.

Table 1. Cat Swarm Optimization summary table

Reference	Publication year	Authors	Solving methods	Problem	Summary
[4]	2018	Gabi, D., Ismail, A. S., Zainal, A., Zakaria, Z., & Al-Khasawneh, A.	Hybrid CSO–SA, Orthogonal Taguchi Method	Dynamic Task Scheduling	Hybrid metaheuristics based on CSO and Simulated Annealing. Dynamic task scheduling, test sets of different sizes (100–1000).
[5]	2021	Zaied, A. N. H., Ismail, M.	Heuristic and metaheuristic methods (GA,	Flow Shop Scheduling variants	A comprehensive literature review on different variants of

		M., & Mohamed, S. S.	PSO, CSO, SA, NEH, etc.)		Flow Shop Scheduling Problems and the solution methods.
[6]	2020	Ahmed, A. M., Rashid, T. A., & Saeed, S. A. M.	CSO and their variants(BCSO, MOCSO, PCSO, HCSO, CSO-GA-SA stb.)	General optimization (survey)	Practical applications of various improved versions of the Cat Swarm Optimization algorithm.
[7]	2025	Tanveer, J. EcoPuma-HFSP	Scheduling models with sustainability considerations	Sustainable Hybrid Flow Shop Scheduling	Sustainability-sensitive hybrid Flow Shop Scheduling Problem with heterogeneous machinery and workforce.
[8]	2021	Pei, X., & Tang, Y.	CSO, EDA-CSO, PSO, BA	Permutation Flow Shop Scheduling	CSO-based solution for PFSP. Comparison with several metaheuristics. Application to the Car benchmark dataset.
[9]	2019	Bouzidi, A., Riffi, M. E., & Barkatou, M.	Cat Swarm Optimization	Open Shop Scheduling	Application of CSO to the Open Shop Scheduling problem. In several cases, it reaches or approaches the best known solutions on Taillard benchmarks.

3.2. Genetic Algorithm

In the article of [10], the authors solve the Hybrid Flow Shop Scheduling task. For this, Genetic Algorithm is used. This is defined in a multiprocessor task environment. The Genetic Algorithm has multiple crossover operators. This method shows better convergence efficiency. The goal of the task is to minimize the makespan. The tasks must pass through processing stages (jobs). Each stage consists of parallel machines. The following crossover operators are used in the Genetic Algorithm: Position Based Crossover (PBX), Order Crossover (OX), Partially Mapped Crossover (PMX), Linear Order Crossover (LOX), Order Based Crossover (OBX). Among the mutation operators, Random Move (RM) and Random Swap (RS) were used. The article examines the efficiencies of each crossover operator on different test data. The test data has the following complexity: m=10,20,50, n=5,10,40,60,80,100. Here m is the number of machines, n is the number of jobs.

In the article [11], the Flow Shop Scheduling was solved with Genetic Algorithm. A distributed, heterogeneous task is presented. The task was solved with a metaheuristic, which is improved multi-population, with a greedy job insertion. In addition, inter-factory neighborhood structure was also applied. The efficiency of the following algorithms was shown in the test results: IG, BCMA, IABC, IMPGA.
In the paper of [12], a Flow Shop Scheduling problem is solved by hybridizing Genetic Algorithm and Tabu Search. The authors of the paper use a new population initialization technique. The algorithm was tested on 120 test datasets, during which it resulted in a better solution in 115 cases than the other tested hybrid algorithms (GA-ISCR, DSOMA, CQGA, TMIIG, IG-JP, HGSA). For example, the following crossover technique was used in the Genetic Algorithm: two-point crossover. The mutation was the swap mutation technique. The entire Taillard dataset was run during the tests.
In the publication of [13], a hybrid Flow Shop Scheduling is solved that takes into account identical machines, sequence-dependent setup times, and machine blocking. It was solved with Genetic Algorithm, where roulette wheel selection, Block Crossover (BX), Uniform Like Crossover (ULX) were used. As the mutation, the swap operator was applied.
In the publication of [14], the authors also solved the Permutation Flow Shop Scheduling problem using the Genetic algorithm. In the article, Deep Reinforcement Learning was used for selection and mutation. The runs were performed on the following test data sizes: $(\mathrm{n}=20, \mathrm{m}=5), (\mathrm{n}=50, \mathrm{m}=10), (\mathrm{n}=100, \mathrm{m}=10)$. The following algorithms were compared in the article: NEH, GNEH, CDS, SA, TS, SHC, VNS, NEGA, On-GPU, DeepRL-GA.
In the paper [15], the authors investigated the Flow Shop Scheduling Problem. The problem is solved using the Non-Dominated Sorting Genetic Algorithm-III (NSGA-III) method because it is a multi-objective optimization problem. The Flow Shop problem also takes energy utilization into account. The authors compared the algorithm with several algorithms, such as Strength Pareto Evolutionary Algorithm 2 (SPEA-II), Pareto Envelope-based Selection Algorithm II (PESA-II), Multi-Objective Particle Swarm Optimization (MOPSO), Multi-objective Evolutionary Algorithm based on Decomposition (MOEA/D). During the hybrid problem, n tasks have to be processed in k steps. Each task can be processed on any level 1 machine, and then they can proceed to any level 2 machine for processing.
In the paper of [16], the authors hybridize the Genetic Algorithm and Penguin Search. The efficiency of the algorithm is examined on the Flow Shop Scheduling problem. The following algorithms were compared: GA (Genetic Algorithm), HWA (Hybrid Whale Optimization Algorithm), IBH (Improved best-so-far heuristic), IHSA (Improved Harmony Search Algorithm), ISDH (Improved std dev heuristic), ISDH-LS (Improved std dev heuristic with local search), MASC (Memetic Algorithm with Novel Semi-Constructive Evolution Operators), NEH (Nawaz-Enscore-Ham), NEH-NGA (Nawaz-Enscore-Ham with Neighborhood Generation Algorithm), NS-SGDE (Self-guided Differential Evolution with Neighborhood Search), PSO (Particle Swarm Optimization), SGA (Standard Genetic Algorithm), SSO (Social Spider Optimization). The Car, Rec and Taillard datasets were used to compare the test results. The algorithms were tested on the following complexity tasks: (n=11, m=5), (n=13, m=4), (n=12, m=5), (n=14, m=4), (n=10, m=6), (n=8, m=9), (n=7, m=7), (n=8, m=8), (n=20, m=5), (n=20, m=5), (n=20, m=5), (n=20, m=10), (n=20, m=10), (n=20, m=10), (n=20, m=15), (n=20, m=15), (n=20, m=15), (n=30, m=10), (n=30, m=10), (n=30, m=10), (n=30, m=10), (n=30, m=10), (n=30, m=15), (n=30, m=15), (n=30, m=15), (n=50, m=10), (n=50, m=10), (n=50, m=10) where n is the number of jobs, m is the number of machines.

In the publication [17], the Flow Shop Scheduling problem is solved using the Genetic Algorithm. The authors used the following crossover operators: Order Crossover with Gene Swapping (OCGS), Order Crossover with Gene Transferring (OCGT), Partially Matched Crossover (PMX). They were run on the following test data of complexity: (m=5, n=10), (m=5, n=30), (m=5, n=60), (m=10, n=10), (m=10, n=30), (m=10, n=60), where m is the number of machines, n is the number of jobs.

In the publication of [18], the authors solve the Flow Shop Scheduling problem using an algorithm that is the combination of Hyena Optimizer and Genetic Algorithm. The authors evaluated this algorithm using test cases from the OR-Library database and compared it with other state-of-the-art optimization methods, such as SSO, SCE-OBL, CLS-BFO, and ACGA. The algorithm is able to find near-optimal solutions with competitive running times. The test runs revealed that the GA-SHOA algorithm outperforms the other algorithms in all cases (REC01–REC23). The algorithms were run for the following complexities: (n=20, m=5), (n=20, m=5), (n=20, m=5), (n=20, m=10), (n=20, m=10), (n=20, m=10), (n=20, m=15), (n=20, m=15), (n=20, m=15), (n=30, m=10), (n=30, m=10), (n=30, m=10) where n is the number of jobs and m is the number of machines.

In [19] publication, the authors solved the Flexible Flow Shop Scheduling problem. Here, they used a type of Genetic Algorithm that is bio-objective. The practical application of the problem is the electrical industry. The goal of the problem is to minimize the makespan and delays, for which the method uses a transfer batch approach. It also considers constraints such as non-identical parallel machines, precedence, release times, and due dates. The GA performed better than the Tabu Search (TS) algorithm.

In [20], the authors solved the Flow Shop Scheduling problem using Genetic Algorithm. They use Precedence Operation Crossover (POX) and swap for mutation.

In [21], the authors apply a combination of Genetic Algorithm and Simulated Annealing for production scheduling. The paper compares the efficiency of three metaheuristics, namely Simulated Annealing, Genetic Algorithm and their combination, Hybrid SA–GA. The algorithms are tested on benchmark examples during the experiments. The tests were conducted for job sizes of 10–200. The efficiency of the algorithms is evaluated based on the following aspects: makespan quality, solution consistency, and computational runtime. Problems of different sizes (10, 25, 75, 100 and 200 jobs) were tested.

In the publication of [22], the authors solve Flow Shop Scheduling problems using Genetic Algorithm. Genetic Algorithm and Campbell Dudek Smith (CDS) method were used fot solving this type of production scheduling problem. The authors also solve a practical example, which is data from a small industrial factory producing jerseys. The data was collected from a manufacturing company located in Bandung, Indonesia.

In [23], the authors solve Flow Shop Scheduling problem using Genetic Algorithm. Reinforcement Learning method was also used. Q-learning is used to learn the crossover probability independently, increasing the efficiency of the Genetic Algorithm. The reward and punishment mechanism are set according to the population values. The authors used Car and Rec databases and compared the results with the traditional Genetic Algorithm (GA) and Adaptive Genetic Algorithm (AGA). The algorithms were tested on the following complex datasets: (n=11, m=5), (n=13, m=4), (n=12, m=5), (n=14, m=4), (n=10, m=6), (n=8, m=9), (n=7, m=7), (n=8, m=8), (n=20, m=5), (n=20, m=5), (n=20, m=5), (n=20, m=10), (n=20, m=10), (n=50, m=10), (n=50, m=10), (n=75, m=20), (n=75, m=20).

In [24], the authors solved the Flow Shop Scheduling problem by hybridizing Grey Wolf and Genetic Algorithm. The tests were performed on 13 Taillard benchmark instances (20–200 jobs, 5–20 machines). The GWO–GA algorithm was the best algorithm compared to the following: SGA, HMSA, NEH, DDE–PFS, DSADE–PFS and DSADEPFS. The Genetic Algorithm has the following operators: Order Crossover (OX), and swap mutation. 2-opt was used as local search.

In [25], the authors also solved the Flow Shop Scheduling problem. The efficiency of the proposed algorithm (a new, multi-objective genetic algorithm, which is the Distance from Ideal Point in Genetic Algorithm (DIPGA)) is compared with other methods: NSGA, MOGA, NSGA-II, WBGA, PAES, GWO, PSO and ACO algorithms. The proposed algorithm was developed by the authors to minimize the makespan (total completion time) and total waiting time. The study used 21 test problems. The number of jobs in the tasks ranged from 20 to 75, while the number of machines ranged from 5 to 20.

In the paper of [26], the authors also solve the Flow Shop Scheduling task. This time, the task is performed in the Green Permutation environment. The combination of Genetic Algorithm and Deep Reinforcement Learning was used to solve the task. The goal of the task is to maximize the completion time (makespan) and minimize the energy consumption. The authors perform test results on 120 test instances of the Taillard standard database. The Standard Genetic Algorithm (SGA), Elite Genetic Algorithm (EGA), Hybrid Genetic Algorithm (HGA), Discrete Self-Organizing Migrating Algorithm (DSOMA), Discrete Water Wave Optimization Algorithm (DWWO) and Hybrid Monkey Search Algorithm (HMSA) with which the authors compared the proposed algorithm.

In the paper of [27], the authors solved the Ordered Flow Shop Scheduling task. Genetic Algorithm was used to solve the problem. The algorithm is compared with other methods such as Nawaz–Enscore–Ham (NEH), pair insert, and iterated local search (ILS). The algorithms were tested on the following complexity datasets: (n=20, m=5), (n=20, m=10), (n=20, m=20), (n=30, m=5), (n=30, m=10), (n=30, m=20), (n=40, m=5), (n=40, m=10), (n=40, m=20), (n=50, m=5), (n=50, m=10), (n=50, m=20), (n=75, m=20), (n=75, m=40), (n=75, m=60), (n=100, m=20), (n=100, m=40), (n=100, m=60), (n=200, m=20), (n=200, m=40), (n=200, m=40), (n=200, m=60), (n=300, m=20), (n=300, m=40), (n=300, m=60), (n=400, m=20), (n=400, m=40), (n=400, m=60), (n=500, m=20), (n=500, m=40), (n=500, m=60), (n=600, m=20), (n=600, m=40), (n=600, m=60), (n=700, m=20), (n=700, m=40), (n=700, m=60), (n=800, m=20), (n=800, m=40), (n=800, m=60), where n is the number of jobs and m is the number of machines. Accordingly, the algorithms were run on small, medium, and large test data.

In the publication of [28], the authors also solve the Flow Shop task. Not a traditional task, but with Rapid Production Rescheduling and Under Machine Failure Disturbance. Here, Genetic Algorithm was also used as the optimization method. The GA is combined with the Hybrid Perturbation Population and ANN (Artificial Neural Networks). The authors designed a rapid production rescheduling framework. The authors use the Perturbation Population Genetic Algorithm (PPGA) algorithm, which is also compared with the standard Genetic Algorithm in terms of performance. The sequence of jobs is the representation mode. The two-point crossover was used for crossover. The swapping operator is used for mutation. The roulette wheel is used for selection. The runs were tested on the Taillard dataset, where the authors present 1-1 test dataset from each complexity of the task.

In the article of [29], the authors also solve the production scheduling task. Here, sustainability aspects are also taken into account when solving the problem.

Periodic electricity prices, worker flexibility, and sequence-dependent setup time are also taken into account when solving the problem. The authors propose an Adjusted Multi-Objective Genetic Algorithm (AMOGA) approach, the running results of which are compared with several algorithms, such as Strength Pareto Evolutionary Algorithm 2 (SPEA2) and Pareto Envelop-based Selection Algorithm 2 (PESA2). The authors had to create a new type of representation mode, where the complete solution includes the order of work, machine selection, worker assignment, and job completion time. The authors also use two crossover operators, such as Partially Matched Crossover (PMX) and Uniform Crossover (UX). In terms of mutation operators, swap, conversion, and insertion were used by the authors.

In the publication of [30], a complex Flow Shop Scheduling with dependent setup time and limited buffers is presented. A dual chain coding scheme and a staged-hierarchical decoding approach are used for efficient representation. This method has a job sequence chain that encodes the sequence of jobs and a machine selection chain that encodes the machine selection. The algorithm uses two initialization methods for the generated initial population. These are HR-JS (Heuristic Rules based on Job Sequence): it generates initial solutions considering the sequence of jobs. DA-MA (Dynamic Adjustment based on Machine Assignment): this method modifies the population by examining the machine assignment. In the crossover phase of the algorithm, two approaches are used, which use the task sequence chain and the machine selection chain, these are Co-SPX (Collaborative Single-Point Crossover) and Co-PMX (Collaborative Partial-Matching Crossover). The authors also used several mutation techniques, such as Single Column Mutation and Column Swap Mutation. Ant Colony Algorithm and Modified Greedy Algorithm with which the efficiency of the algorithm was also compared. The test instances were randomly generated, the details are as follows: the number of tasks: 30, 50, 80, 100, 150, 200. The number of stages was 2 and 3. The number of cycles was 2 and 3. The number of machines in each stagewas 3 and 4.

In the paper of [31], the authors solve the Flow Shop Scheduling problem. Here, the authors developed an algorithm based on a combination of NEH and Niche Genetic Algorithm (NEH-NGA). The algorithm has the following characteristics: NEH algorithm is used to optimize the initial population. The Genetic Algorithm contains three different crossover operators. Niche procedure is used to control the population distribution. The algorithms were tested on different benchmark data sets. The developed algorithm was also compared with the NEH and SGA algorithms. The tests were validated on benchmark data. The authors demonstrated the efficiency of the algorithm on small, medium and large problem sizes. The following problem sizes were also tested: (n=20, m=20), (n=50, m=5), (n=50, m=20), (n=100, m=5), (n=100, m=10), (n=200, m=10) (n=200, m=20), where n is the number of jobs, m is the number of machines.

In the article [32], the authors discuss a hybrid version of the Flow Shop Scheduling problem, which is of multi-objective distributed type. The problem is solved using the Dual-Population Genetic Algorithm with Q-Learning algorithm. The authors discuss a distributed Hybrid Flow Shop Scheduling problem, where the problem is to minimize the maximum completion time and the number of late jobs. The test results were also compared with several other algorithms, such as NSGA-II (Non-dominated Sorting Genetic Algorithm II) and SPEA2 (Strength Pareto Evolutionary Algorithm 2).

Table 2. Genetic Algorithm summary table

Reference	Publication year	Authors	Solving methods	Problem	Summary
[10]	2023	Guan, Y., Chen, Y., Gan, Z., Zou, Z., Ding, W., Zhang, H., ... & Ouyang, C.	Genetic Algorithm (multi-crossover)	Hybrid Flow Shop Scheduling	GA-based solution for HFSP in a parallel machine environment. Makespan minimization, investigation of the efficiency of different crossover operators.
[11]	2023	Cui, H., Li, X., & Gao, L.	Improved Multi-population GA + greedy insertion	Distributed Flow Shop Scheduling	An improved multi-population Genetic Algorithm in a heterogeneous, distributed Flow Shop environment with inter-factory neighborhood structure.
[12]	2022	Umam, M. S., Mustafid, M., & Suryono, S.	Hybrid GA–Tabu Search	Flow Shop Scheduling	Hybridization of AGA and Tabu Search with a new initialization method. Tested on Taillard dataset.
[13]	2022	Maciel, I. S. F., Prata, B. D. A., Nagano, M. S., & Abreu, L. R. D.	Genetic Algorithm	Hybrid Flow Shop Scheduling	Complex HFSP that takes into account identical machines, sequence-dependent setup times, and blocking.
[14]	2023	Irmouli, M., Benazzoug, N., Adimi, A. D., Rezkellah, F. Z., Hamzaoui, I., Hamitouche, T., ... & Tayeb, F. S.	Genetic Algorithm + Deep Reinforcement Learning	Permutation Flow Shop Scheduling	GA-based solution where selection and mutation are supported by deep reinforcement learning. Comparison with several classical heuristics.
[15]	2023	Mu'Tasim, M. A. N., & Rashid, M. F. F. A.	NSGA-III	Multi-objective Flow Shop Scheduling	Multi-objective Flow Shop Problem considering

					energy consumption, using NSGA-III and comparing it with other multi-objective algorithms.
[16]	2024	Mzili, T., Mzili, I., Riffi, M. E., Pamucar, D., Simic, V., Abualigah, L., & Almohsen, B.	Hybrid GA–Penguin Search	Flow Shop Scheduling	A hybridization of GA and Penguin Search, which shows competitive results against other state-of-the-art algorithms on multiple benchmark datasets.
[17]	2025	Fichera, S., Grasso, V., Lombardo, A., & Valvo, E. L.	Genetic Algorithm	Flow Shop Scheduling	Examining the effects of different crossover operators. Using test data of different sizes.
[18]	2023	Mzili, T., Mzili, I., Riffi, M. E., & Dhiman, G.	Hybrid GA–Hyena Optimizer (GA-SHOA)	Flow Shop Scheduling	Hybrid algorithm based on GA and Hyena Optimizer. OR-Library benchmark datasets.
[19]	2024	Escobar, D., Chivata, B., & Nino, K.	Bi-objective Genetic Algorithm	Flexible Flow Shop Scheduling	Bio-objective GA application in Flexible Flow Shop environment. Minimizing makespan and delays.
[20]	2023	Nhu, P. N., Thi, K. N. N., & Thi, T. H. T. V.	Genetic Algorithm	Flow Shop Scheduling	GA with POX crossover and swap mutation to solve the Flow Shop Scheduling problem.
[21]	2025	SEDOUD, A., & HASSAM, A.	Hybrid SA–GA	Production Scheduling	Simulated Annealing, Genetic Algorithm and hybrid SA–GA methods on scheduling benchmarks of different sizes.
[22]	2024	Prassetiyo, H.,	Genetic	Flow Shop	GA and CDS

		& Heryati, F.	Algorithm + CDS	Scheduling	method for Flow Shop Scheduling problem, with presentation of a real industrial (textile) case study.
[23]	2022	Gao, X., Yang, S., & Li, L.	Genetic Algorithm + Q-learning	Flow Shop Scheduling	Reinforcement learning-supported GA. Crossover probability is learned adaptively by Q-learning.
[24]	2025	Mzili, M., Torki, M., Mzili, T., Mijwil, M. M., Amine, M. B., Annuk, A., & Waga, A.	Hybrid GWO–GA	Flow Shop Scheduling	Hybridization of Grey Wolf Optimizer and GA on Taillard benchmarks.
[25]	2024	Shahsavari-Pour, N., Heydari, A., Fekih, A., & Asadi, H.	Multi-objective GA (DIPGA)	Flow Shop Scheduling	A new multi-objective Genetic Algorithm. Makespan and waiting time minimization.
[26]	2025	Lu, Y., Yuan, Y., Yasenjiang, J., Sitahong, A., Chao, Y., & Wang, Y.	GA + Deep Reinforcement Learning	Green Permutation Flow Shop	Combination of GA and Deep Reinforcement Learning. Energy efficient Flow Shop Scheduling problem.
[27]	2025	Cubukcuoglu, A., Karacan, I., Ceylan, Z., & Bulkan, S.	Genetic Algorithm	Ordered Flow Shop Scheduling	GA-based solution to the Ordered Flow Shop problem, on small, medium, and large test data.
[28]	2023	Saophan, P., Pannakkong, W., Singhaphandu, R., & Huynh, V. N	PPGA + ANN	Flow Shop Scheduling under Machine Failure	A fast rescheduling framework for machine failures. A combination of perturbation population GA and neural network.
[29]	2023	Mokhtari-Moghadam,	Adjusted Multi-	Sustainable Production	Application of multi-objective

		A., Pourhejazy, P., & Gupta, D.	objective GA (AMOGA)	Scheduling	GA taking into account sustainability aspects in addition to energy prices, labor and SDST.
[30]	2024	Zheng, Q., Zhang, Y., Tian, H., & He, L.	Genetic Algorithm (dual-chain coding)	Complex Flow Shop Scheduling	Complex Flow Shop problem. Special encoding and decoding helps to apply GA effectively.
[31]	2022	Liang, Z., Zhong, P., Liu, M., Zhang, C., & Zhang, Z.	NEH + Niche Genetic Algorithm	Flow Shop Scheduling	GA enhanced with NEH-based initialization and Niche Strategy. It outperforms the base GA on several benchmarks.
[32]	2023	Zhang, J., & Cai, J.	Dual-Population GA + Q-learning	Distributed Hybrid Flow Shop Scheduling	The GA applied to a multi-objective, distributed HFSP, employing population management supported by Q-learning.

4. Summary

This article presents two metaheuristic algorithms and the most important published papers for a production scheduling task, which is Flow Shop Scheduling. These two algorithms are Cat Swarm Optimization and Genetic Algorithm. Both algorithms are population-based algorithms, which means that they maintain and continuously improve a population of solutions. They are inspired by nature, one by cat behavior, the other by genetics and reproduction. The article presents the results from Google Scholar and Elsevier databases, followed by the most important papers and their summary in tabular form.

Based on the literature, it can be stated that the Genetic Algorithm (GA) and its improved and hybrid versions play a decisive role in solving flow shop problems. The GA effectively solves the direction of more complex, heterogeneous and distributed manufacturing environments, as well as scheduling problems that take into account multi-objective and sustainability aspects, through basic flow shop problems. GA also effectively solves tasks involving various machine constraints, setup times, blocking conditions, machine errors, energy consumption and other practical factors. In the literature, we can also find numerous hybridizations that combine the genetic algorithm with Tabu Search, Simulated Annealing, Grey Wolf Optimizer, Penguin Search or other search strategies. The common goal of these approaches is to alleviate the classical limitations of GA: accelerating convergence, avoiding local optima and traversing the search space more efficiently.

Another significant development direction, according to the literature, is the integration of adaptive and learning-based GA approaches, such as Q-learning, Deep Reinforcement Learning or neural networks into the genetic algorithm. These solutions allow certain algorithm parameters – such as the crossover probability, selection or mutation operation – to change not in a pre-fixed way, but based on information obtained during the search process.

It is also clear from the research that the objective functions used are becoming increasingly complex, and in many places researchers have already used the combined use of several objective functions. In addition to production time, optimization of energy consumption, waiting time, delays, labor costs, energy prices, and more general sustainability aspects is also appearing.

Overall, the literature shows that the genetic algorithm, combined with other metaheuristics, remains a viable and competitive method for dealing with complex scheduling problems. Future research should explore additional algorithms for production scheduling tasks.

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EKÖP Egyetemi Kutatói Ösztöndíj Program

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