ISSN: 0974-5823 Vol. 7 No. 2 February, 2022

International Journal of Mechanical Engineering

Optimization Algorithms for Integrated Process Planning and Scheduling: A Review

Muhammed A Mahdi[1, a] , Lamyaa Mohammed Dawood [1, b]

[1]*Productuin Engineering and Metallurgy*
University of Technology - Iraq.

Abstract. *"process planning" and scheduling are two highly important subsystems in the manufacturing environment, the Integration of both of them can led to optimize the production productivity and to minimizing the production cost, that is an important factor for successful the manufacturing environment, To solving "integrated process planning and scheduling" (IPPS) many optimization methods used because it form the most difficult combinatory problem and needed efficient methods to find optimal solution, in this review various eminent researchers implemented different optimization algorithms, researchers are recommended as Artificial Intelligent various algorithms directions for future .*

INTRODUCTION

Market needs are increasingly various and meet them some manufacturing firms have planned a high-mixture of product manufacturing with few quantity strategy. The Flexible manufacturing production arrangement seems a usual direction in fabrication companies [1]. Many research studies deals with the field of flexible manufacturing systems [2],condense on process planning, job shop scheduling. The "process planning" modelled by computer implementation went to be more importantly essential, that because minimization the duration to fabricate, design and maximize flexibility of product life stages. The versatility of production machine equipment and "process planning" greatly increase the flexibility of frim production. But consequent with high complexity of "job shop scheduling" [3]. So that the relation between product design and product manufacturing, product process planning mange the fabrication technique, order of the processing, fabrication variables, resources of the shop , time of fabrication, and other circumstances [4].

Scheduling of job shop define by logical assignment of the fabrication supplies and the fulfillment of efficiency indexes to the production criteria that gathering "process planning" and processing constraints. The important activity that control and plan of manufacturing processes done by the scheduling which can be manage to make better sustainability in working shop [5][6][7] [8].

As always process planning and the scheduling of job shop are controlled by a stand-alone departments for the manufacturing process. Together They executed one by one in sequence: the process planning after release from the planner engineer must have a completed job shop scheduling [9] [10].

The relationship between "process planning" and scheduling are Overlapped, "integrated process planning and scheduling" (IPPS) recently take the center of attention academicals studies [11]. Outcome appear the IPPS may achieve requirements to find the best utilization resources to minimization of costs, minimize production bottlenecks, and enhance production system productivity beside visible improvement in the manufacturing system's performance. The IPPS treated as NP-hard problem. Progression engaged integration become progressive in the increment of complexity to solve the algorithm. The optimum solution to a huge extent IPPS problem with the deterministic algorithm [12]. Researchers implement a wide types of heuristic algorithms in with the effort to optimize the IPPS, and several steps has been reached, but to find an algorithm satisfactory for a huge extent IPPS problem may need more studied.

OPTIMIZATION ALGORITHMS

Recent space of optimization, finding solution of the optimization ordinary is to achieve the optimal for the problem variables according the problem objective which are maximization or minimization for numbers of problem objective function without violating the problem constraints. The typical optimization problems may have some obstacles, such as cost of high computation, constraints with non -linear finites, search environment with non-convex, objective functions with dynamic to noisy behavior , and solution space for large problems [13].

The essential criteria for choosing either the exact (deterministic) or the approximate algorithms (stochastic) to solve complicated real problems. Even if algorithms are can offering the ideal global solution altogether, The result demonstrates an exponentially increased similarity of the set of variables[14].

Important criteria for selecting either exact (deterministic) or approximate (stochastic) algorithms for helping solve real problems. Even if a perfect algorithm is able to peer into all of the intricacies of the optimal solution, the amount of time it takes is exponential, since it will need to recognize all of the parameters. [15].

There are two types of optimization algorithms, the former which involve optimization methods based on nature, and the latter which involve optimization methods based on natural principles. While algorithms are completely first place, in that category examples. such as, adaptive dimensional search (ADS) [16], tabu search (TS) [17] , and iterated local search (ILS) [18], a lot of meta-heuristic optimization algorithms have been mimic the nature.

The optimization algorithms inspired by nature were came in first such as, Gravitational Search Algorithm (GSA) [19] Particle Swarm Optimization (PSO) [20], Artificial Bee Colony (ABC) [21], and differential evolution (DE)[22], Krill Herd (KH) [23].

They are modular and scalable, because they can solve difficult problems by constantly exploring the space of solutions. Beside, several metaheuristics like Ant Colony Optimization (ACO) [24][25][26] and Genetic Algorithm (GA) [27][28], were came first to solve binary and combinatorial problems.

Solving optimization problems have been widely used for that algorithms which are grouped by three classes: Evolutionary Algorithms, Physics based algorithms, and Swarm Intelligence algorithms. Evolutionary algorithms (EAs) act for a set of iterative algorithms of optimization that simulates nature evolution [14]. In order to form a new generation, the best individuals are combined, which is the key robustness of EAs as it improved the population's development over the iterations[27]. Trying to imitate the development of Darwin, Evolution Strategy (ES) [29], Genetic Programming (GP) [30] and Differential Evolution (DE) [22]. Physics-based algorithms simulated physical bases of the nature where individuals communicate in the searching space by the use of laws and physics bases such as molecular mechanics, law of refraction, force of light inertia, and force of gravitation. Gravitational search algorithms are several well-known algorithms of this genre (GSA)[19], Charged System Search (CSS) [31], Ray Optimization (RO) [32]. Swarm intelligence algorithms (SIs) the mass attitude of social animals such as ants' foraging, bird flocking, and animal herding is influenced by them. Through collaboration and interaction, all species shift multilaterally into the positive areas of the searching space. The famous algorithms that are already well in this class are Particle Swarm Intelligence (PSO) [20] [33] [34], Artificial Bee Colony (ABC) [21], Krill Herd (KH) [23], Grey Wolf Optimizer (GWO) [35], Whale Optimization Algorithm (WOA) [36]. While swarm smart algorithms have proved to be efficient in addition to solving optimization problems, they can suffer from trapping the solutions in a local optimum, early convergence, and dropping them. Therefore, proposals have been made to change SI difference algorithms in order to strengthen their vulnerabilities. The Comprehensive Learning Particle Swarm Optimizer (CLPSO) [37] Jumping from local optima was stated, and the DEWCO [38] Using a hyper-heuristic to enhance the initial sets of WOA to increase its speed of convergence. Besides, the Conscious Neighborhood-Based Crow Search Algorithm (CCSA) [39] A balance stalemate for the locally and globally search.

INTEGRATED PROCESS PLANNING AND SCHEDULING

Topic of "integration of process planning and scheduling" started by late-1980s Chryssolouris and Chan [40] Initially is introduced the notion of process planning and scheduling integration. In comparison Beckendorff [41] alternate process plans are then used to improve the versatility in the method. In addition to taking on the principle of alternate process paths and complex input response, the integrated model proposed by Zhang [42] and Larsen [43] reflects a belief of structured management to an established level. Scientists later introduced a lot of research into the "integration of "process planning" and scheduling" for the job shop, and created some integration models and methodological approaches to enhance the integration of process planning and scheduling research[44].

The IPPS will explain as: granting a selection of *n* parts to be fabricated with suitable alternative process plans, manufacturing supplies, and other technical requirements on *m* machines, selecting an acceptable process plan and manufacturing supplies, and operation sequence to find the timeframe for meeting the technological constraints for operations and achieving the goals [45].

When the introduced researches in the field of Computer Integrated Manufacturing (CIMS), It has been recognized that IPPS is so essential in the progression of process of CIM [46], some models of IPPS have been conducted by researchers. Some literature studies and reviews have classified IPPS models into three basic categories: - : Non-Linear "process planning" (NLPP), Closed-Loop "process planning" (CLPP) , and Distributed "process planning" (DPP) [44].

The Non-Linear "Process Planning" (NLPP) approach is to adapt all alternate process plans with ranking numbers for each variable to the optimization criterion for "process planning." When the job is required, the process plan with the highest ranking according to the priority is still ready for process. If the first-priority process plan is not suitable for the current shop floor status, the second-priority process plan with the highest ranked numbers will be added to the scheduling system. Figure 1 illustrates the basic NLPP flowchart. The "process planning" scheme and scheduling framework are completely segregated between each other on the basis of the standard NLPP flowchart. NLPP only uses alternate process plans to increase the production system's flexibility.

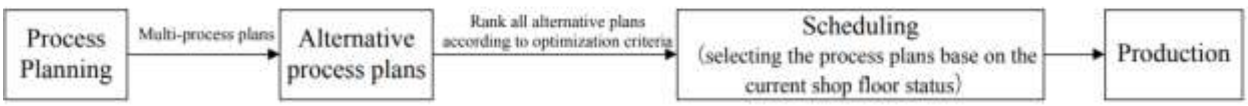

Figure 1 Flowchart of NLPP [44]

The approach of Closed-Loop "process planning" (CLPP) uses a hierarchical framework of "process planning" with a feedback technique. By way of dynamic input from the development scheduling system, CLPP will bring in a real-time process schedule. The strategy of 'method preparation' brings in process strategies dependent on existing tools. Production scheduling includes details on the machines are available for incoming work for processing on the shop floor, meaning that any schedule must be practical and complies with the actual supply of production machines[44] the simple flowchart of CLPP is shown in Figure 2.

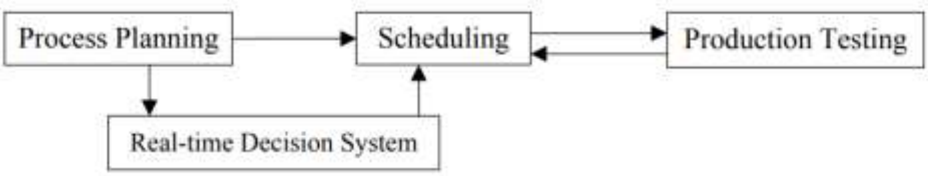

Figure 2 Flowchart of CLPP [44].

The Distributed "Process Planning" (DPP) approach uses the principle of a simultaneous engineering approach to concurrently incorporate both "process planning" and scheduling. The preparation and arranging process was split down to two stages. The preliminary planning process is the first step. The properties of parts and the linkage between the parts are verified at this point. And, there are collections of original process plans and schedule plans. There are also parallel projections of the process supplies. The second stage is the comprehensive preparation stage, which has been broken into two phases: the subsequent planning process and the final planning phase. In this step, the process plans controlled in the shop floor to the current condition [44] the basic flowchart of NLPP is shown in Figure 3.

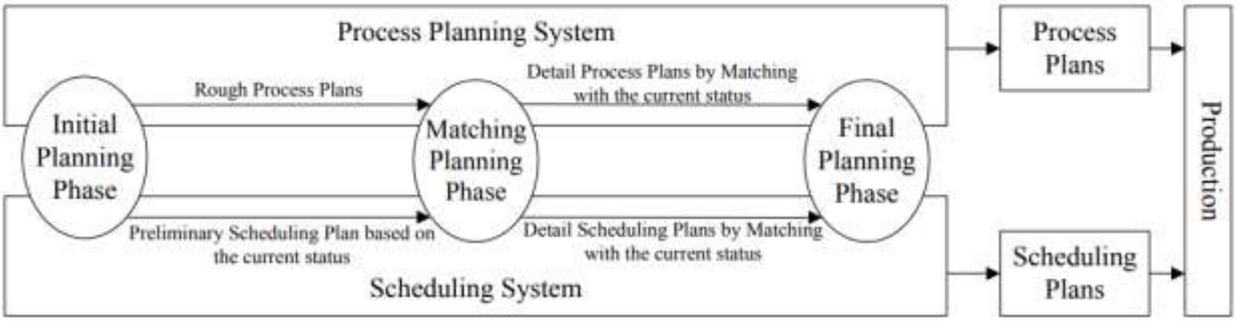

Figure 3 Flowchart of DPP [44].

OPTIMIZATION ALGORITHMS OF IPPS

A lot of research work has been conducted on it in order to improve the solution consistency of IPPS, and to address the issues more efficiently and effectively. The right form has not yet been discovered, however. To focus at developing efficient algorithms [47][48]. To address IPPS, several Artificial Intelligence (AI)-based methods have been developed. Several standard approaches will be reviewed in the following pages.

Exact Algorithms

The Researchers have implemented several precise IPPS solution algorithms, most of which are formulated using Integer Linear Programming (ILP) or Mixed ILP (MILP) models. The mathematical techniques which are reviewed in have been mentioned along with the referred article.

These are the most techniques used for solving IPPS. These mathematical optimization methods are described as follows:

Designing an integrated process and scheduling, in most mathematical models have used two sets of ordered pairs that show precedence or non-precedence relations between operations, which is conceptually correct but is not solvable using optimization software. And applying a different approach of mixed integer programming (MIP) then solved by GAMS software [49].

A linearized polynomial mixed-integer programming model (PMIPM) for the integration of “process planning” and scheduling was developed a promising procedure to linearize the PMIPM and to convert it into an equivalent linear mixed-integer programming, it is a promising procedure to linearize the PMIPM and to convert it into an equivalent linear mixed-integer programming problem [50].

Present two models to realize a comparison between the two most interesting ones, using the standard solver CPLEX, and determine a production plan for a given sequence of operations in the resources while considering constraints such as setup times and costs and lead time, The difference between the models is, the non-consideration of the backlog cost, The performance of the proposed algorithms was evaluated on a set of instances [51].

A flexible assembly job shop with sequence dependent setup times was modeled as a mixed integer linear programming model to minimize makespan dependent on Non-Linear process planning methodology for IPPS problem which generates process and scheduling plans simultaneously [52].

Implementation and deployment of a MIP mathematical model that integrates the IPPS and the consideration of tasks' setup time. In sequence dependent setup time (SDST) scheduling problems setup time depending on the sequential order of jobs processed on each machine.[53].

Evolutionary Algorithms

Evolutionary algorithms are subject of optimization algorithms which are based on the biological evolution. As the name implies, evolutionary computational methods are designed on the principles of evolution. They are based on the Darwinian evolution philosophy of the fittest and use selection, mating, reproduction, crossover, and mutation operators similar as the biological processes of evolution. Genetic algorithm (GA) and differential evolution (DE) [54] such as:

Genetic algorithm (GA)

GA emulates the techniques of evolution that have been in existence for millions of years in nature. When an algorithm is designed based on natural genetics it will be able to solve complex problems with simple techniques in finite time. genetic algorithm is the most used optimization algorithm for solving "integrated process planning and scheduling" as: mathematical modeling and genetic algorithm [55], comparison genetic algorithm [56], rescheduling genetic algorithm [57], benchmark genetic algorithm [58], pure genetic algorithm [59] [60], simulation based genetic algorithms [61], active learning genetic algorithm [62], hybrid genetic algorithm [63], multi-objective genetic algorithm [64], modified genetic algorithm [65], alternant iterative genetic algorithm [66], and genetic algorithm derived from immune principle [67], non-dominated sorting genetic algorithm (NSGA-II) [64], modern genetic algorithms proved to be very reliable in finding optimal process plans and schedule [68].

Swarm Intelligence Algorithms

Computational intelligence (CI) is a subset of machine learning and artificial intelligence that collectively refers to algorithms with intelligence built into them. Most of the evolutionary algorithms and swarm intelligence algorithms have computational intelligence built into them. Some of the popular computational intelligence algorithms are neural networks, fuzzy logic, differential evolution, particle swarm optimization, firefly algorithm, ant colony optimization, and other swarm-based algorithms. Nature-inspired [54]. as: comparison simulated annealing [56], Ant Lion Optimization (ALO) [69], Ant colony optimization (ACO) [70], colonial competitive algorithm (CCA) [71], honey bee mating optimization (HBMO) algorithm [72], particle swarm optimisation (PSO) algorithm [73], hybrid particle swarm optimization (PSO) [74], simulated annealing-based algorithm [75].

CONCLUSION

This paper reviews some of the optimization algorithms used for solving "integrated process planning and scheduling" Although various algorithms have been applied to solve the integration of process planning and scheduling problem and several researchers have examined many algorithms, it's obvious the most used algorithm is genetic algorithm due to its properties, in recent years Nature-inspired algorithms is gaining more interesting due to the number of new introduced algorithms based on Nature-inspired, hybrid algorithms used to tune solution for better optimal solution, integration more subsystem to increase the collaboration for the manufacturing system such as logistics and maintenance, with the higher increase in data and information technology such as Industry 4.0 and internet of things (IOT) more constrains can be processed due to the capabilities of new artificial intelligent tools to mimic the real industry problems especially IPPS.

REFERENCES

1. [1] K. Abd, K. Abhary, and R. Marian, "Efficient scheduling rule for robotic flexible assembly cells based on fuzzy approach," *Procedia CIRP*, vol. 3, no. 1, pp. 483–488, 2012, doi: 10.1016/j.procir.2012.07.083.
2. [2] K. Abd, K. Abhary, and R. Marian, "Multi-objective optimisation of dynamic scheduling in robotic flexible assembly cells via fuzzy-based Taguchi approach," *Comput. Ind. Eng.*, vol. 99, pp. 250–259, 2016, doi: 10.1016/j.cie.2016.07.028.
3. [3] K. Abd, K. Abhary, and R. Marian, "Simulation modelling and analysis of scheduling in robotic flexible assembly cells using Taguchi method," *Int. J. Prod. Res.*, vol. 52, no. 9, pp. 2654–2666, 2014, doi: 10.1080/00207543.2013.867082.
4. [4] X. Zhang, Z. Liao, L. Ma, and J. Yao, "Hierarchical multistrategy genetic algorithm for integrated process planning and scheduling," *J. Intell. Manuf.*, 2020, doi: 10.1007/s10845-020-01659-x.

5. [5] Z. T. Jabur and L. Dawood, “Analysis of Information Flow for Job-Shop Production System,” *Eng. &Tech.Journal*, vol. 33, no. 1, pp. 223–236, 2015.
6. [6] M. A. Mahmoud, “Developing Multistage Heuristic Algorithm to Minimize Idle Time and Make Span in Job Shop Scheduling,” *Eng. &Tech.Journal*, vol. 28, no. 14, pp. 4789–4806, 2010.
7. [7] K. Abd, K. Abhary, and R. Marian, “Scheduling and Performance Evaluation of Robotic Flexible Assembly Cells under Different Dispatching Rules,” *Adv. Mech. Eng.*, vol. 1, no. 1, pp. 31–40, 2011.
8. [8] Z. T. Jebur and L. Dawood, “Analysis of Information Flow for Job-Shop Production System,” *Eng. &Tech.Journal*, vol. 33 A, no. 1, pp. 223–236, 2015, doi: 10.13140/RG.2.2.22478.31045.
9. [9] J. M. Usher and K. J. Fernandes, “Dynamic process planning — The static phase,” *J. Mater. Process. Technol.*, vol. 61, no. 1–2, pp. 53–58, Aug. 1996, doi: 10.1016/0924-0136(96)02465-X.
10. [10] F. I. Telchy and S. Rafaat, “Intelligent Neural Network with Greedy Alignment for Job-Shop Scheduling,” *Iraqi J. Comput. Commun. Control Syst. Eng.*, vol. 15, no. 3, 2015.
11. [11] N. Bassim and L. A. Al-kindi, “AN INTEGRATED METHODOLOGY FOR TIME REDUCTION IN JOB SHOP ENVIRONMENT,” vol. 3, no. 2, pp. 176–192, 2009.
12. [12] Y. K. Kim, K. Park, and J. Ko, “A symbiotic evolutionary algorithm for the integration of process planning and job shop scheduling,” *Comput. Oper. Res.*, vol. 30, no. 8, pp. 1151–1171, 2003, doi: 10.1016/S0305-0548(02)00063-1.
13. [13] I. Fister Jr, X.-S. Yang, I. Fister, J. Brest, and D. Fister, “A brief review of nature-inspired algorithms for optimization,” *arXiv Prepr. arXiv1307.4186*, 2013.
14. [14] E.-G. Talbi, *Metaheuristics: from design to implementation*, vol. 74. John Wiley & Sons, 2009.
15. [15] K. Sörensen, “Metaheuristics—the metaphor exposed,” *Int. Trans. Oper. Res.*, vol. 22, no. 1, pp. 3–18, 2015.
16. [16] O. Hasançebi and S. K. Azad, “Adaptive dimensional search: a new metaheuristic algorithm for discrete truss sizing optimization,” *Comput. Struct.*, vol. 154, pp. 1–16, 2015.
17. [17] F. Glover, “Tabu search—part I,” *ORSA J. Comput.*, vol. 1, no. 3, pp. 190–206, 1989.
18. [18] H. R. Lourenço, O. C. Martin, and T. Stützle, “Iterated local search: Framework and applications,” in *Handbook of metaheuristics*, Springer, 2019, pp. 129–168.
19. [19] E. Rashedi, H. Nezamabadi-Pour, and S. Saryazdi, “GSA: a gravitational search algorithm,” *Inf. Sci. (Ny).*, vol. 179, no. 13, pp. 2232–2248, 2009.
20. [20] R. Eberhart and J. Kennedy, “A new optimizer using particle swarm theory,” in *MHS’95. Proceedings of the Sixth International Symposium on Micro Machine and Human Science*, 1995, pp. 39–43.
21. [21] D. Karaboga and B. Basturk, “A powerful and efficient algorithm for numerical function optimization: artificial bee colony (ABC) algorithm,” *J. Glob. Optim.*, vol. 39, no. 3, pp. 459–471, 2007.
22. [22] R. Storn and K. Price, “Differential evolution–a simple and efficient heuristic for global optimization over continuous spaces,” *J. Glob. Optim.*, vol. 11, no. 4, pp. 341–359, 1997.
23. [23] A. H. Gandomi and A. H. Alavi, “Krill herd: a new bio-inspired optimization algorithm,” *Commun. nonlinear Sci. Numer. Simul.*, vol. 17, no. 12, pp. 4831–4845, 2012.
24. [24] M. Dorigo, M. Birattari, and T. Stutzle, “Ant colony optimization,” *IEEE Comput. Intell. Mag.*, vol. 1, no. 4, pp. 28–39, 2006.
25. [25] S. M. Raafat, “Advanced Optimization and Intelligent Methods for Engineering Applications,” in *2018 Third Scientific Conference of Electrical Engineering (SCEE)*, 2018, p. 334, doi: 10.1109/SCEE.2018.8684071.
26. [26] H. Al-Khazraji, S. Khlil, and Z. Alabacy, “Industrial picking and packing problem: Logistic management for products expedition,” *J. Mech. Eng. Res. Dev.*, vol. 43, no. 2, pp. 74–80, 2020.
27. [27] J. H. Holland, “Genetic algorithms,” *Sci. Am.*, vol. 267, no. 1, pp. 66–73, 1992.
28. [28] A. Al-Zuheri, L. Luong, and K. Xing, “Developing a multi-objective genetic optimisation approach for an operational design of a manual mixed-model assembly line with walking workers,” *J. Intell. Manuf.*, vol. 27, no. 5, pp. 1049–1065, 2016, doi: 10.1007/s10845-014-0934-3.
29. [29] I. Rechenberg, “Evolution strategy: Optimization of technical systems by means of biological evolution,” *Fromman-Holzboog, Stuttgart*, vol. 104, pp. 15–16, 1973.
30. [30] J. Kosa, *Genetic Programming*. 1997.
31. [31] A. Kaveh and S. Talatahari, “A novel heuristic optimization method: charged system search,” *Acta Mech.*, vol. 213, no. 3, pp. 267–289, 2010.

32. [32] A. Kaveh and M. Khayatazad, “A new meta-heuristic method: ray optimization,” *Comput. Struct.*, vol. 112, pp. 283–294, 2012.

33. [33] A. M. Hasan and S. M. Rafaat, “Optimized formation control of multi-agent system using PSO algorithm,” *Indones. J. Electr. Eng. Comput. Sci.*, vol. 20, no. 3, pp. 1591–1600, 2020, doi: 10.11591/ijeecs.v20.i3.pp1591-1600.

34. [34] L. H. Abood, E. H. Karam, and A. H. Issa, “FPGA Implementation of Single Neuron PID Controller for Depth of Anesthesia Based on PSO,” in *2018 Third Scientific Conference of Electrical Engineering (SCEE)*, 2018, pp. 247–252, doi: 10.1109/SCEE.2018.8684186.

35. [35] S. Mirjalili, S. M. Mirjalili, and A. Lewis, “Grey wolf optimizer,” *Adv. Eng. Softw.*, vol. 69, pp. 46–61, 2014.

36. [36] S. Mirjalili and A. Lewis, “The whale optimization algorithm,” *Adv. Eng. Softw.*, vol. 95, pp. 51–67, 2016.

37. [37] J. J. Liang, A. K. Qin, P. N. Suganthan, and S. Baskar, “Comprehensive learning particle swarm optimizer for global optimization of multimodal functions,” *IEEE Trans. Evol. Comput.*, vol. 10, no. 3, pp. 281–295, 2006.

38. [38] M. Abd Elaziz and S. Mirjalili, “A hyper-heuristic for improving the initial population of whale optimization algorithm,” *Knowledge-Based Syst.*, vol. 172, pp. 42–63, 2019.

39. [39] H. Zamani, M. H. Nadimi-Shahraki, and A. H. Gandomi, “CCSA: conscious neighborhood-based crow search algorithm for solving global optimization problems,” *Appl. Soft Comput.*, vol. 85, p. 105583, 2019.

40. [40] W. Tan and B. Khoshnevis, “Integration of process planning and scheduling—a review,” *J. Intell. Manuf.*, vol. 11, no. 1, pp. 51–63, 2000.

41. [41] U. Beckendorff, J. Kreutzfeldt, and W. Ullmann, “Reactive workshop scheduling based on alternative routings,” in *Proceedings of a conference on factory automation and information management*, 1991, pp. 875–885.

42. [42] H.-C. Zhang and M. E. Merchant, “IPPM–a prototype to integrate process planning and job shop scheduling functions,” *CIRP Ann.*, vol. 42, no. 1, pp. 513–518, 1993.

43. [43] N. E. Larsen, “Methods for integration of process planning and production planning,” *Int. J. Comput. Integr. Manuf.*, vol. 6, no. 1–2, pp. 152–162, 1993.

44. [44] X. Li and L. Gao, *Effective methods for integrated process planning and scheduling*, vol. 2. Springer, 2020.

45. [45] Y. W. Guo, W. D. Li, A. R. Mileham, and G. W. Owen, “Optimisation of integrated process planning and scheduling using a particle swarm optimisation approach,” *Int. J. Prod. Res.*, vol. 47, no. 14, pp. 3775–3796, 2009, doi: 10.1080/00207540701827905.

46. [46] T. Wei and B. Khoshnevis, “Integration of process planning and scheduling: a review,” *J. Intell. Manuf.*, vol. 3052, no. April, pp. 51–63, 2000, doi: 10.1080/0951192X.2011.562543.

47. [47] M. Liu, S. Yi, and P. Wen, “Quantum-inspired hybrid algorithm for integrated process planning and scheduling,” vol. 232, no. 6, pp. 1105–1122, 2016, doi: 10.1177/0954405416661006.

48. [48] M. Liu, S. Yi, and P. Wen, “Quantum-inspired hybrid algorithm for integrated process planning and scheduling,” 2016, doi: 10.1177/0954405416661006.

49. [49] M. Saidi and S. Zarghami, “Exact Mixed Integer Programming for Integrated Scheduling and Process Planning in Flexible Environment,” vol. 15, pp. 47–53, 2014.

50. [50] W. Tan and B. Khoshnevis, “A linearized polynomial mixed integer programming model for the integration of process planning and scheduling,” *J. Intell. Manuf.*, vol. 15, no. 5, pp. 593–605, 2004, doi: 10.1023/B:JIMS.0000037710.80847.b6.

51. [51] Z. I. M. Hassani, A. El Barkany, A. Jabri, and I. El Abbassi, “Models for solving integrated planning and scheduling problem: Computational comparison,” *Int. J. Eng. Res. Africa*, vol. 34, pp. 161–170, 2018, doi: 10.4028/www.scientific.net/JERA.34.161.

52. [52] S. Nourali, N. Imanipour, and M. R. Shahriari, “A mathematical model for integrated process planning and scheduling in flexible assembly job shop environment with sequence dependent setup times,” *Int. J. Math. Anal.*, vol. 6, no. 41–44, pp. 2117–2132, 2012.

53. [53] S. Altarazi and O. Yasin, “Integration of process planning and scheduling with sequence dependent setup time: A case study from electrical wires and power cable industry,” *Adv. Intell. Syst. Comput.*, vol. 360, pp. 283–294, 2015, doi: 10.1007/978-3-319-18167-7_25.

54. [54] A. Vasuki, *Nature-Inspired Optimization Algorithms*. Chapman and Hall/CRC, 2020.

55. [55] X. Li, L. Gao, X. Shao, C. Zhang, and C. Wang, “Mathematical modeling and evolutionary algorithm-based approach for integrated process planning and scheduling,” *Comput. Oper. Res.*, vol. 37, no. 4, pp. 656–667, 2010, doi: 10.1016/j.cor.2009.06.008.

56. [56] A. R. Botsalı, “Comparison of Simulated Annealing and Genetic Algorithm Approaches on Integrated Process Routing and Scheduling Problem,” *Int. J. Intell. Syst. Appl. Eng.*, vol. 4, no. Special Issue-1, pp. 101–104, 2016, doi: 10.18201/ijisae.267358.
57. [57] A. R. Botsalı, “A Scheduling and Rescheduling Algorithm for Integrated Process Planning and Scheduling Problem,” vol. 4, no. 4, pp. 7122–7130, 2017.
58. [58] H. R. Choi and B. J. Park, “Genetic algorithm for the integration of process planning and scheduling in a job shop,” *WSEAS Trans. Inf. Sci. Appl.*, vol. 3, no. 12, pp. 2498–2504, 2006.
59. [59] M. D. G. Optimization and B. Landwehr, “A Genetic Algorithm based Approach for,” no. August, pp. 305–339, 2014.
60. [60] X. Li, L. Gao, G. Zhang, C. Zhang, and X. Shao, “A genetic algorithm for integration of process planning and scheduling problem,” *Intell. Robot. Appl.*, pp. 495–502, 2008.
61. [61] H. Lee and S.-S. Kim, “Integration of Process Planning and Scheduling Using Simulation Based Genetic Algorithms,” *Int. J. Adv. Manuf. Technol.*, vol. 18, no. 8, pp. 586–590, 2001, doi: 10.1007/s001700170035.
62. [62] X. Li, L. Gao, and X. Shao, “An active learning genetic algorithm for integrated process planning and scheduling,” *Expert Syst. Appl.*, vol. 39, no. 8, pp. 6683–6691, 2012, doi: 10.1016/j.eswa.2011.11.074.
63. [63] X. Li, X. Shao, L. Gao, and W. Qian, “An effective hybrid algorithm for integrated process planning and scheduling,” *Int. J. Prod. Econ.*, vol. 126, no. 2, pp. 289–298, 2010, doi: 10.1016/j.ijpe.2010.04.001.
64. [64] P. Mohapatra, L. Benyoucef, and M. K. Tiwari, “Integration of process planning and scheduling through adaptive setup planning: A multi-objective approach,” *Int. J. Prod. Res.*, vol. 51, no. 23–24, pp. 7190–7208, 2013, doi: 10.1080/00207543.2013.853890.
65. [65] X. Shao, X. Li, L. Gao, and C. Zhang, “Integration of process planning and scheduling-A modified genetic algorithm-based approach,” *Comput. Oper. Res.*, vol. 36, no. 6, pp. 2082–2096, 2009, doi: 10.1016/j.cor.2008.07.006.
66. [66] H. Sen Yan, X. Q. Wan, and F. L. Xiong, “Integrated production planning and scheduling for a mixed batch job-shop based on alternant iterative genetic algorithm,” *J. Oper. Res. Soc.*, vol. 66, no. 8, pp. 1250–1258, 2015, doi: 10.1057/jors.2014.88.
67. [67] G. Luo, X. Wen, H. Li, W. Ming, and G. Xie, “An effective multi-objective genetic algorithm based on immune principle and external archive for multi-objective integrated process planning and scheduling,” *Int. J. Adv. Manuf. Technol.*, vol. 91, no. 9–12, pp. 3145–3158, 2017, doi: 10.1007/s00170-017-0020-z.
68. [68] M. Milošević, D. Lukić, M. Đurđev, J. Vukman, and A. Antić, “Genetic algorithms in integrated process planning and scheduling–a state of the art review,” *Proc. Manuf. Syst.*, vol. 11, no. 2, pp. 83–88, 2016.
69. [69] M. Petrović, J. Petronijević, M. Mitić, N. Vuković, Z. Miljković, and B. Babić, “The Ant Lion Optimization Algorithm for Integrated Process Planning and Scheduling,” *Appl. Mech. Mater.*, vol. 834, pp. 187–192, 2016, doi: 10.4028/www.scientific.net/amm.834.187.
70. [70] L. Zhang and T. N. Wong, “Solving integrated process planning and scheduling problem with constructive meta-heuristics,” *Inf. Sci. (Ny).*, vol. 340–341, pp. 1–16, 2016, doi: 10.1016/j.ins.2016.01.001.
71. [71] Y. Lian, L. Meng, Y. Wang, C. Zhang, Y. Wei, and K. Lian, “A Hybrid Colonial Competitive Algorithm for the Integrated Process Planning and Scheduling Problem,” in *2020 International Conference on Urban Engineering and Management Science (ICUEMS)*, 2020, pp. 117–123, doi: 10.1109/ICUEMS50872.2020.00035.
72. [72] L. Jin, C. Zhang, and X. Shao, “An effective hybrid honey bee mating optimization algorithm for integrated process planning and scheduling problems,” *Int. J. Adv. Manuf. Technol.*, vol. 80, no. 5, pp. 1253–1264, 2015, doi: 10.1007/s00170-015-7069-3.
73. [73] Y. W. Guo, W. D. Li, A. R. Mileham, and G. W. Owen, “Applications of particle swarm optimisation in integrated process planning and scheduling,” *Robot. Comput. Integr. Manuf.*, vol. 25, no. 2, pp. 280–288, 2009, doi: 10.1016/j.rcim.2007.12.002.
74. [74] M. Yu, Y. Zhang, K. Chen, and D. Zhang, “Integration of process planning and scheduling using a hybrid GA/PSO algorithm,” *Int. J. Adv. Manuf. Technol.*, vol. 78, no. 1, pp. 583–592, 2015, doi: 10.1007/s00170-014-6669-7.
75. [75] W. D. Li and C. A. McMahon, “A simulated annealing-based optimization approach for integrated process planning and scheduling,” *Int. J. Comput. Integr. Manuf.*, vol. 20, no. 1, pp. 80–95, Jan. 2007, doi: 10.1080/09511920600667366.