International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

Application of Heuristics in Logistics and Job-Shop Scheduling

Indranil Deb [a], ***Ranjan Kumar Gupta*** [b*]

[a] Research Scholar, Department of Management and Commerce, West Bengal State University, Barasat, Kolkata-700124, India

[b*] Assistant Professor, Department of Management and Marketing, West Bengal State University, Barasat, Kolkata-700124, India

DOI- https://doi.org/10.55248/gengpi.4.523.40014

ABSTRACT

The development of heuristics techniques has emerged over the years to address complex decision-making process in the various fields of social sciences. With many advantages of heuristics, there are few disadvantages also, which should be carefully handled to arrive at the decision or solution. The researchers have put enormous effort to develop heuristics model integrating with the nature-inspired algorithm. Development of heuristics has made it easy to formulate and to solve various complex real-life problems including some of the well-known supply-chain problems. Due to change in the business environment, the activities related to procuring raw material and delivery of finished goods are tied cohesively. As a result, now job-shop scheduling is not a discrete supply-chain problem. It is linked with inventory of raw materials, inventory of finished products and just-in-time delivery of goods through right channels. Another crucial aspect of supply-chain domain is to build integrated and effective logistics system which is popularly known as vehicle routing problem.

Key Words: Heuristics, job-shop scheduling, vehicle routing, logistics systems

1. Introduction

The heuristic method refers to finding the best possible solution to a problem quickly, effectively, and efficiently. The word heuristic is derived from an ancient Greek word, '**eurisko**.' It means to find, discover, or search. It is a practical method of mental shortcut for problem-solving and decision making that reduces the cognitive load and does not require to be perfect. The method is helpful in getting a satisfactory solution to a much larger problem within a limited time frame. Heuristics are problem-solving techniques that result in a quick and practical solution. In contrast to business decisions that involve extensive analysis, heuristics are used in situations where a short-term solution is required. Nobel-prize winning economist and cognitive psychologist Herbert Simon originally introduced the concept of heuristics in psychology in the 1950s. He suggested that while people strive to make rational choices, human judgment is subject to cognitive limitations. Purely rational decisions would involve weighing all the potential costs and possible benefits of every alternative. Heuristics play important roles in both problem-solving and decision-making, as we often turn to these mental shortcuts when we need a quick solution. We probably make hundreds or even thousands of decisions every day. Heuristics allow us to make such decisions with relative ease and without a great deal of agonizing. Heuristics allow us to think through the possible outcomes quickly and arrive at a solution.

Context of Heuristics

There are many kinds of heuristics. Based on different contexts, each type plays a role in decision-making. The various contexts of heuristics are availability, familiarity, representativeness, affect, anchoring, scarcity, and trial & error.

Advantages of Heuristics

Some of the advantages of heuristics can be described as follows:

a) **Speed:** Heuristics model can be applied to provide a dependable way to make search algorithms faster and more efficient to make decisions within a short time. Heuristics way of thinking help us to arrive at the best decision, considering the circumstances and available information.

b) **Versatility:** Heuristics have a wide range of applications, from daily living to professional fields like computer science, social engineering, medical systems and so on. Applying a heuristic model allows to improve the functions of the algorithms and to obtain feedback early in the design process.

c) **Economical:** Heuristics contributes to efficiency, creative thinking, and problem-solving skills; as it enables to adapt effectively within available factors, variables, information, or available options. Heuristics allows to make quick and sound decisions with the few factors at disposal.

Disadvantages of Heuristics

a) **Bias:** The major pitfall of applying heuristics is its likelihood of encouraging bias. Heuristics model helps to think quickly based on the assumptions about the future using past events. This assessment can affect to determine the real value.

b) **Inaccuracy:** Heuristics are instrumental in making various decisions, the speed and faulty information involved may lead to inaccurate judgments, assumptions, and choices. Heuristics can make the decision susceptible to sensational and inaccurate information.

c) **Dependent Patterns:** Heuristics are vital to make quick decisions, but the temptation can arise after easing into a pattern of fast decisions. Rational decisions usually require to consider all the available factors along with the goal. It is important to avoid cycles of quick and inaccurate decisions by considering the implications of using heuristics when opportunities for more effective decisions present themselves.

2. Literature review

According to Glover (1997), meta-heuristics "refers to a master strategy that guides and modifies other heuristics to produce solutions beyond those that are normally generated in a quest for local optimality". Basically, a meta-heuristic is a top-level strategy that guides an underlying heuristic solving a given problem. Glover and Laguna (1997) further defined meta-heuristics as "it in their modern forms are based on a variety of interpretations of what constitutes intelligent search". We may also consider the following definition: "a meta-heuristic is an iterative generation process which guides a subordinate heuristic by combining intelligently different concepts for exploring and exploiting the search spaces using learning strategies to structure information in order to find efficiently near-optimal solutions", (Osman & Kelly, 1996). There are several important meta-heuristics which originated from different settings such as psychology ("learning"), biology ("evolution"), physics ("annealing"), and neurology ("nerve impulses") have served as a starting point. There are many local search based meta-heuristics like Greedy Randomized Adaptive Search (replicating a search procedure to determine a local optimum), the pilot method (look ahead mechanism of the pilot method is related to increased neighborhood depths to exploit the evaluation of neighbour at larger depths to guide the neighbor selection at depth one), variable neighborhood search (changing the neighborhood during the search in a systematic way and explores increasingly distant neighborhoods of the current incumbent solution and finds a new solution, if an improvement has been made). The simulated annealing (SA) extends basic local search by allowing moves to inferior solutions. The basic algorithm of SA may be described as follows: successively a candidate move is randomly selected; this move is accepted if it leads to a solution with a better objective function value than the current solution, otherwise the move is accepted with a probability that depends on the deterioration of the objective function value.

Simulated annealing is further developed to overcome performing deteriorating moves when no improving moves exist. At each iteration a best admissible neighbor may be selected. Tabu search (TS) overcome this limitation by guiding local search approaches reaching local optimality. This is done by a dynamic transformation of the local neighborhood. TS used in many forms based on move attributes and tabu navigation method.

Various Evolutionary algorithms applied to solve heuristics problems in diversified areas. These concepts consist of genetic algorithms (Goldberg, 1989) and (Holland, 1975), evolutionary strategies (Hoffmiester & Back, 1991), evolutionary programs (Fogel, 1993), scatter search (Glover, 1977 & 1995), memetic algorithms (Moscato, 1993), ant-colony optimization (Dorigo et al, 1996); Stutzle & Hoos (1999), Taillard (2000), and particle swarm optimization etc. Genetic algorithms are a class of adaptive search procedures based on the principles derived from the dynamics of natural population genetics. One of the most crucial ideas for a successful implementation of a genetic algorithm (GA) is the representation of an underlying problem by a suitable scheme. One of the recently explored concepts within intelligent search is the ant system, a dynamic optimization process reflecting the natural interaction between ants, searching for food. The ants' ways are influenced by two different kinds of search criteria. The first one is the local visibility of food and the second one is based on the fact that each ant's way through its food space is affected by the other ants' trails as indicators for possibly good directions.

3. Application of heuristics in job-shop scheduling

Many decision-making problems in business and economics including those in manufacturing, location routing, transport, scheduling, and inventory may be formulated as optimization problems. These problems are too difficult to solve within a reasonable amount of time. In those scenarios, heuristics become the method of choice to obtain a quality of solution. Due to the complexity of many of the optimization problems, where exact algorithms often perform poorly, heuristic algorithms are conspicuously preferable in those practical applications. Heuristics applied as a local search approach has been developed to improve given feasible solutions. To overcome the drawback of continuing search beyond local optima, meta-heuristics like tabu search is applied to solve optimization problems.

The job-shop scheduling is a well-known classical problem. Due to its complexity and wide applications, many researchers have paid attention. Most researchers have focused on minimization of the makespan, while less attention paid on other scheduling criteria (Braune, Zäpfel, & Affenzeller, 2012). Braune et. al. proposed method for single machine scheduling problems of weighted tardiness job shops. They factored other parameters like delayed precedence constraints, multiple local due dates per operation and an objective function with a weighted sum of maximum tardiness values. Bennell et. al. (2017) and Boysen et. al. (2015) further introduced the performance of the real-world systems and operations.

Cheng et. al. (2021) applied heuristics method to solve just-in-time job-shop (JIT-JSS) scheduling problem to determine operation completion time. The variable neighbourhood search (VNS) is applied to solve JIT-JSS to generate a schedule. The problem of job-shop scheduling has many variants like measurement of customer satisfaction as a function of tardiness (Zhou, Cheung, & Leung, 2009), reducing the warehousing and inventory costs by minimizing functions of earliness (Wan & Yen, 2009). In a job-shop scheduling problem the target is to minimize the completion of each operation within stipulated schedule. We can classify just-in-time manufacturing into two categories, one is completion of jobs within due dates and the other one is completion of operation level (Bürgy & Bülbül, 2018) within due dates. The researchers applied tabu search heuristics to minimize cost functions for operation start time and the differences between the start times of arbitrary pairs of operations. Over a period, various researchers formulated earliness-tardiness job-shop scheduling problem from various aspects, where they applied linear programming, hybrid solution algorithm (Beck & Refalo, 2003), large neighbourhood search (Danna, Rothberg, & Le Pape, 2003), cost directed initialization (Kelbel & Hanzálek, 2007; Kelbel & Hanzálek, 2011) etc. In job-shop scheduling, machine breakdown time and inventory cost for the operations are two important aspects. To fine optimal release time, one should target to minimize the tardiness and inventory cost together. Al-Salem, Bedoya-Valencia, and Rabadi (2016) developed dynamic programming algorithm for two-machine job-shop scheduling problem with a common due-date for a set of jobs.

To solve JIT-JSS problem heuristics and meta-heuristics technique have also been applied by many researchers. Araujo, dos Santos, and Arroyo (2009) developed a genetic algorithm, which was further developed by formulating hybrid method evolutionary algorithm to find the optimal schedule for a given sequence. Wang and Li (2014) applied a similar approach to that of Dos Santos et al. (2010) and formulated a mathematical programming model with variable neighbourhood search (VNS) algorithm to evaluate the sequences and to optimally schedule the jobs in a given sequence.

4. Application of heuristics in logistics/vehicle routing problem

One of the critical and significant aspect of supply chain management is vehicle routing problem (VRP) or logistics (Zhang & Gui et. al., 2021). Globalization and international trade have instigated for the development of global logistics and supply chains. Vehicle routing problem is very crucial part of supply chain, to develop a good logistics system. The dynamic and stochastic vehicle routing problems have received attention in the last two decades. This problem is to minimize the traveling distance of vehicles under the condition that every customer must be serviced by a vehicle (Hashimoto, Hu, Okamoto, 2022). It also comprises of schedule of the vehicles along with the routes. The routing of the vehicles depends on many parameters and priorities within the supply chain. The vehicle route scheduling problem commonly formulated as a liner programming problem, though many heuristics methodologies like local search methods, the cross-exchange neighborhood and the Or-opt neighborhood have also been applied. The vehicle routing problem raises concern when it comes for distribution of perishable goods maintaining its quality. The problem gets more complicated when dynamic order processing is considered in real scheduling environment (Zhang et. al., 2022). Many aspects have been incorporated into this problem, like minimizing loss of vehicles, refrigeration consumption, cargo damage (Hu & Qi, 2020), multi-depot VRP to minimize the total cost of fresh products distribution, minimization of carbon emission (Lim et. al., 2020; Tseng et. al., 2019; Zhou et. al. 2019) etc. Further Wang et. al. (2018) reformulated muti-depot VRP and distribution location together.

The ant colony optimization (ACO) and its variant named ant colony system (ACS) have been used to solve many combinatorial real-world optimization problems (Zhan et. al., 2022 & Zhang et. al., 2022). Sangaiah et. al. (2018) developed metaheuristics method based on Adaptive Large Neighborhood Search (ALNS) algorithm, to solve Dynamic Vehicle Routing Problem (DVRP) with limited vehicles and hard-time windows. Yang et. al. (2017) worked on variant of vehicle routing problem with dynamically changing orders and time windows. In real-world, during operation time, often demands change - new orders placed and others are canceled. To address this scenario, to generate new schedules on-the-fly, a multiple ant colony algorithm combined with powerful local search procedures is proposed with time windows. This problem is further twisted by introducing minimum cost routes of a similar vehicles to meet the demand within time windows, while order from new customers can be allocated to vehicles (Reimann et. al., 2021). Considering known customers, static route is prepared first and then routes are re-optimized repeatedly either continuously or periodically. A different aspect of delivery can be priority of the customers, where priority customers are served earlier compared to non-priority customers. Barma et. al., 2022 applied a hybrid metaheuristic, based on Greedy Randomized Adaptive Search Procedure (GRASP) and Non-dominated Sorting Genetic Algorithm (NSGAII) to minimize customers' average latency along with minimum distance traveled by all the vehicles. The vehicle routing problem can be looked upon from different angle, where environment is a critical factor due to heavy vehicle movement. Yagmur & Kesen (2023) combined vehicle routing problem with production scheduling. Their objective was to minimize the total amount of CO_2 emitted by the vehicles and to minimize the maximum tardiness resulting from late deliveries. To build vehicle routing mechanism, it is essential to consider acquisition cost of the vehicles, where vehicles can be composed of various types like electric and conventional cars. Masmoudi et. al. (2022) introduces number of vehicles and combination of vehicles to plan a set of different vehicle routes to serve a set of clients. This type of situation comes in real life when clients may require multiple visits within specified time window. The researchers presented a mixed integer linear-programming formulation and developed a multi-start Adaptive Large Neighborhood Search with threshold accepting algorithm.

To mention a few meta-heuristics technique, inspired from nature, like Flower Pollination optimization (Zhou et. al., 2016), Brain storm optimization (Huang et. al., 2016; Ke, 2018; Chen et. al., 2019; Dolicanin et. al., 2018), Whale optimization algorithm (Mirjalili & Lewis, 2016), Pigeon-inspired optimization (Zhang et. al., 2019; Duan et. al., 2018), Elephants Herding optimization (Coelho et. al., 2015), and Rhino herd behavior (Zenger et. al., 2018) etc. have been applied to vehicle routing optimization. Though few nature-inspired biological phenomena have been applied to VRP, but those are yet to be explored further. There is an opportunity to work on these recent metaheuristics methods and to apply to complex formulation of the VRP.

5. Relevance of the study

The relevance of this study is to explore the development and formulation of job-shop scheduling problem and vehicle routing problem over the years and to demonstrate how various methodologies have been applied to solve these problems. Our objective can be summarized as below:

- Review the literature of job-shop scheduling problem and vehicle routing problem.
- Identify the types of job-shop scheduling problem and related constraints in various phases of production environment.
- Development of logistics from discrete environment to integrated logistics systems.
- Identify the methodologies used by various researchers to optimize various constraints in different complex real-life situation.
- Application of different heuristics techniques contributed to the solution of diversified and integrated job-shop scheduling problem and vehicle routing problem.

6. Research Gap

Researchers may focus on to improve and upgrade the existing research methods to obtain better scheduling results. Each algorithm has its own advantages and disadvantages. Different methodologies can be combined to solve the job shop scheduling problem more efficiently. Integrating different research methods, researchers can complement various research methods in solving job shop scheduling problems. The dynamic nature of job-shop scheduling problem has increased its complexity many folds. The job-shop scheduling problem should be integrated with multi-machines, multi-resources with multiple factories and logistics systems. Thus, we should shift our focus to smart distributed scheduling modeling and optimization. Hence, there is an ample opportunity to optimize production schedule with other domain of supply chain and formulate job-shop scheduling problem

The vehicle routing problem can be investigated further by introducing available resources to operate the vehicles. Among the fleet of available vehicles, the performance of each vehicle cannot be same. This factor can be introduced in the problem by considering the maximum distance that can be covered by a vehicle within specified time window. Heuristics approach of cost minimization of total delivery system may be formulated within a specific geographical area with a combination of few large and many small vehicles of different energy system. Due to necessity of global supply chain framework, a very large-scale real-world optimization has emerged as a promising area to develop and to solve vehicle routing problem. Building a large-scale logistics system require coordination among global players to share their services for mutual benefit. Sharing information timely within the supply chain actors ensure smooth transportation across the globe. To achieve these objectives, multitask optimization (Gupta et. al., 2016), multifactorial evolution (Feng et. al., 2015) and federated optimization technique (McMahan et. al., 2016) can be applied for better result.

7. Conclusion

This paper studies relevant articles on job-shop scheduling problem and vehicle routing problem, the two important domains of supply chain management. Our study reveals that, with the increasing complexity of supply chain management, both problems have shifted their nature from discrete to integrated environment. Initially both the problems have been formulated in isolation where each stage is locally optimized. Growing demand and integrated natured of business environment have compelled to explore these in different ways. In these scenarios, the focus shifted from local optimization to global search and optimization. The integration of sub-systems was not much effective to achieve global optimization, where development of heuristics and combination of multiple methodologies have evolved and transformed the solution at optimum level. With the advancement of technology and growing demand of just-in-time delivery, there is further opportunity to look at the job-shop and vehicle routing problem in a different manner, which is outlined in the section of research gap.

8. References

1. T. Sang Le, T. P. Nguyen, H. Nguyen and H. Q. T. Ngo; "Integrating Both Routing and Scheduling Into Motion Planner for Multivehicle System," in *IEEE Canadian Journal of Electrical and Computer Engineering*, vol. 46, no. 1, pp. 56-68, winter 2023, doi: 10.1109/ICJECE.2022.3218929.
2. Ece Yağmur & Saadettin Erhan Kesen; Bi-objective coordinated production and transportation scheduling problem with sustainability: formulation and solution approaches, International Journal of Production Research, 61:3, 774-795, 2023, DOI: 10.1080/00207543.2021.2017054.
3. Z. H. Zhan et al., "Matrix-based evolutionary computation;" IEEE Trans. Emerg. Top. Comput. Intell., vol. 6, no. 2, pp. 315–328, Feb. 2022.
4. Partha Sarathi Barma, Joydeep Dutta, Anupam Mukherjee & Samarjit Kar; A bi-objective latency based vehicle routing problem using hybrid GRASP-NSGAII algorithm, International Journal of Management Science and Engineering Management, 2022, DOI: 10.1080/17509653.2022.2076168.
5. Z. H. Zhan, L. Shi, K. C. Tan, and J. Zhang; "A survey on evolutionary computation for complex continuous optimization," Artif. Intell. Rev., vol. 55, no. 1, pp. 59–110, 2022.
6. Mohamed Amine Masmoudi, Manar Hosny & Çağrı Koç; The fleet size and mix vehicle routing problem with synchronized visits, Transportation Letters, 14:4, 427-445, 2022, DOI: 10.1080/19427867.2021.1888196.

7. H. Hashimoto, Y. Hu and Y. Okamoto; "An Efficient Route Evaluation Method for the Vehicle Routing Problem with Linear Constraints," *2022 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM)*, Kuala Lumpur, Malaysia, 2022, pp. 0511-0515, doi: 10.1109/IEEM55944.2022.9989917.

8. L. -J. Wu, L. Shi, Z. -H. Zhan, K. -K. Lai and J. Zhang; "A Buffer-Based Ant Colony System Approach for Dynamic Cold Chain Logistics Scheduling," in *IEEE Transactions on Emerging Topics in Computational Intelligence*, vol. 6, no. 6, pp. 1438-1452, Dec. 2022, doi: 10.1109/TETCI.2022.3170520.

9. Mohammad Mahdi Ahmadian, Amir Salehipour, T.C.E. Cheng; A meta-heuristic to solve the just-in-time job-shop scheduling problem, European Journal of Operational Research, Volume 288, Issue 1, 2021, Pages 14-29, ISSN 0377-2217, https://doi.org/10.1016/j.ejor.2020.04.017.

10. da Silva Júnior, O.S., Leal, J.E. & Reimann M; A multiple ant colony system with random variable neighborhood descent for the dynamic vehicle routing problem with time windows. *Soft Comput* **25**, 2935–2948, 2021. https://doi.org/10.1007/s00500-020-05350-4.

11. Y. L. Lan, F. G. Liu, W. W. Y. Ng, J. Zhang, and M. K. Gui; “Decomposition based multi-objective variable neighborhood descent algorithm for logistics dispatching,” IEEE Trans. Emerg. Top. Comput. Intell., vol. 5, no. 5, pp. 826–839, Apr. 2021.

12. C. M. Qi and L. S. Hu; “Optimization of vehicle routing problem for emergency cold chain logistics based on minimum loss,” Phys. Commun., vol. 40, pp. 1–7, 2020.

13. G. K. Liu, J. Y. Hu, Y. Yang, S. M. Xia, and M. K. Lim; “Vehicle routing problem in cold chain logistics: A joint distribution model with carbon trading mechanisms,” Resour. Conservation Recycling, vol. 156, pp. 1–13, 2020.

14. Y. Li, M. K. Lim, and M. L. Tseng; “A green vehicle routing model based on modified particle swarm optimization for cold chain logistics,” Ind. Manage. Data Syst., vol. 119, no. 3, pp. 473–494, 2019.

15. Mofid-Nakhaee, E., Barzinpour, F.: A multi-compartment capacitated arc routing problem with intermediate facilities for solid waste collection using hybrid adaptive large neighborhood search and whale algorithm. Waste Management & Research 37(1), 2019, 38–47.

16. J. Chen, P. F. Gui, T. Ding, S. Y. Na, and Y. T. Zhou; “Optimization of transportation routing problem for fresh food by improved ant colony algorithm based on tabu search,” Sustainability, vol. 11, no. 23, pp. 1–22, 2019.

17. Wu, L., He, Z., Chen, Y., Wu, D., Cui, J.: Brainstorming-based ant colony optimization for vehicle routing with soft time windows. IEEE Access 7, 2019, 19643–19652.

18. Arora, S., Singh, S.; Butterfly optimization algorithm: a novel approach for global optimization. Soft Computing 23(3), 2019, 715–734 225.

19. Hu, C., Xia, Y., Zhang, J.: Adaptive operator quantum-behaved pigeon-inspired optimization algorithm with application to uav path planning. Algorithms 12(1), 2019, 3.

20. Zhang, D., Duan, H.: Social-class pigeon-inspired optimization and time stamp segmentation for multi-uav cooperative path planning. Neurocomputing 313, 2018, 229–246.

21. S. Y. Wang, F. M. Tao, and Y. H. Shi; “Optimization of location–routing problem for cold chain logistics considering carbon footprint,” Int. J. Environ. Res. Public Health, vol. 15, no. 1, pp. 1–17, 2018.

22. Wang, G.G., Gao, X.Z., Zenger, K., Coelho, L.d.S.; A novel metaheuristic algorithm inspired by rhino herd behavior. In: Proceedings of The 9th EUROSIM Congress on Modelling and Simulation. Number 142, Linkoping University Electronic Press, 2018, 1026–1033.

23. Bürgy, Reinhard, and Kerem Bülbül; "The job shop scheduling problem with convex costs." *European Journal of Operational Research* 268.1, 2018, 82-100.

24. S. F. Chen, R. Chen, G. G. Wang, J. Gao, and A. K. Sangaiah; “An adaptive large neighborhood search heuristic for dynamic vehicle routing problems,” Comput. Elect. Eng., vol. 67, pp. 596–607, 2018.

25. Ke, L.; A brain storm optimization approach for the cumulative capacitated vehicle routing problem. Memetic Computing 10(4) (2018) 411–421.

26. Dolicanin, E., Fetahovic, I., Tuba, E., Capor-Hrosik, R., Tuba, M.; Unmanned combat aerial vehicle path planning by brain storm optimization algorithm. Studies in Informatics and Control 27(1), 2018, 15–24.

27. Z. Yang et al.; “Dynamic vehicle routing with time windows in theory and practice,” Natural Comput., vol. 16, no. 1, pp. 119–134, 2017.

28. Bennell, Julia A., Mohammad Mesgarpour, and Chris N. Potts; "Dynamic scheduling of aircraft landings." *European Journal of Operational Research* 258, no. 1, 2017, 315-327.

29. Horng, M.F., Dao, T.K., Shieh, C.S., et al.; A multi-objective optimal vehicle fuel consumption based on whale optimization algorithm. In: Advances in Intelligent Information Hiding and Multimedia Signal Processing. Springer, 2017, 371–380 198.

30. Ong, Y.S., Gupta, A.; Evolutionary multitasking: a computer science view of cognitive multi-tasking. Cognitive Computation 8(2), 2016, 125–142 221.
31. Konecnˇ y, J., McMahan, H.B., Ramage, D., Richt`arik, P.; Federated optimization: Distributed ´ machine learning for on-device intelligence. arXiv preprint arXiv:1610.02527. 2016.
32. Kaveh, A., Zolghadr, A.: A novel meta-heuristic algorithm: tug of war optimization. Iran University of Science & Technology 6(4), 2016, 469–492 224.
33. Al-Salem, M., Bedoya-Valencia, L., & Rabadi, G; Heuristic and exact algorithms for the two-machine Just in Time job shop scheduling problem. *Mathematical Problems in Engineering*, 11. 2016, doi: 10.1155/2016/6591632.
34. Yan, X., Hao, Z., Huang, H., Li, G.: Human-computer cooperative brain storm optimization algorithm for the two-echelon vehicle routing problem. In: 2016 IEEE Congress on Evolutionary Computation (CEC), IEEE, 2016, 2676–2681 188.
35. Mirjalili, S., Lewis, A.; The whale optimization algorithm. Advances in engineering software 95, 2016, 51–67 28 Osaba et al. 197.
36. Gupta, A., Ong, Y.S., Feng, L.; Multifactorial evolution: toward evolutionary multitasking. IEEE Transactions on Evolutionary Computation 20(3), 2015, 343–357 222.
37. Wang, G.G., Deb, S., Coelho, L.d.S.: Elephant herding optimization. In: 2015 3rd International Symposium on Computational and Business Intelligence (ISCBI), IEEE, 2015, 1–5.
38. Zhou, Y., Wang, R.: An improved flower pollination algorithm for optimal unmanned undersea vehicle path planning problem. International Journal of Pattern Recognition and Artificial Intelligence 30(04), 2016, 1659010.
39. Nils Boysen, Simon Emde, Michael Hoeck, Markus Kauderer; Part logistics in the automotive industry: Decision problems, literature review and research agenda, European Journal of Operational Research, Volume 242, Issue 1, 2015, Pages 107-120, ISSN 0377-2217, https://doi.org/10.1016/j.ejor.2014.09.065.
40. Braune, Roland & Zäpfel, Günther & Affenzeller, Michael; An exact approach for single machine subproblems in shifting bottleneck procedures for job shops with total weighted tardiness objective. European Journal of Operational Research. 218, 76-85, 2012, 10.1016/j.ejor.2011.10.020.
41. Kelbel, J., Hanzálek, Z.; Solving production scheduling with earliness/tardiness penalties by constraint programming. J. Intell. Manuf. **22**(4), 553–562, 2011.
42. Zhou, Hong, Waiman Cheung, and Lawrence C. Leung. "Minimizing weighted tardiness of job-shop scheduling using a hybrid genetic algorithm." *European Journal of Operational Research* 194.3, 2009, 637-649.
43. R. P. Araujo, A. G. dos Santos and J. E. C. Arroyo; "Genetic algorithm and local search for just-in-time job-shop scheduling," *2009 IEEE Congress on Evolutionary Computation*, Trondheim, Norway, 2009, pp. 955-961, doi: 10.1109/CEC.2009.4983048.
44. Guohua Wan, Benjamin P.-C. Yen; Single machine scheduling to minimize total weighted earliness subject to minimal number of tardy jobs, European Journal of Operational Research, Volume 195, Issue 1, 2009, Pages 89-97, ISSN 0377-2217, https://doi.org/10.1016/j.ejor.2008.01.029.
45. Kelbel, J., Hanzálek, Z.; "Constraint programming search procedure for earliness/tardiness job shop scheduling problem". In: Proceedings of the 26th Workshop of the UK Planning and Scheduling Special Interest Group, pp. 67–70, 2007.
46. Beck, J.C., Refalo, P. A Hybrid; Approach to Scheduling with Earliness and Tardiness Costs. *Annals of Operations Research* **118**, 49–71, 2003, https://doi.org/10.1023/A:1021849405707.
47. Danna, Emilie, Edward Rothberg, and Claude Le Pape; "Integrating mixed integer programming and local search: A case study on job-shop scheduling problems." Fifth international workshop on integration of AI and or techniques in constraint programming for combinatorial optimisation problems (CP-AI-OR'2003). 2003.
48. E. Taillard; An introduction to ant systems. In M. Laguna and J.L. Gonzalez Velarde, editors, Computing Tools for Modeling, Optimization and Simulation, pages 131–144. Kluwer, Boston, 2000.
49. T. St¨utzle and H. Hoos; The max-min ant system and local search for combinatorial optimization problems. In S. Voss, S. Martello, I.H. Osman, and C. Roucairol, editors, Meta-Heuristics: Advances and Trends in Local Search Paradigms for Optimization, pages 313–329. Kluwer, Boston, 1999.
50. H.-P. Schwefel and T. B¨ack; Artificial evolution How and why? In D. Quagliarella, J. P´eriaux, C. Poloni, and G. Winter, editors, Genetic Algorithms and Evolution Strategyin Engineering and Computer Science: Recent Advances and Industrial Applications, pages 1–19. Wiley, Chichester, 1998.

51. F. Glover and M. Laguna; Tabu Search. Kluwer, Boston, 1997.
52. I.H. Osman and J.P. Kelly; editors. Meta-Heuristics: Theory and Applications. Kluwer, Boston, 1996.
53. M. Dorigo, V. Maniezzo, and A. Colorni; Ant system: Optimization by a colony of cooperating agents. IEEE Transactions on Systems, Man and Cybernetics, B - 26:29–41, 1996.
54. Glover, F; Scatter search and star-paths: beyond the genetic metaphor. OR Spektrum 17, 125–137, 1995, https://doi.org/10.1007/BF01719256.
55. D.B. Fogel; On the philosophical differences between evolutionary algorithms and genetic algorithms. In D.B. Fogel and W. Atmar, editors, Proceedings of the Second Annual Conference on Evolutionary Programming, pages 23–29. Evolutionary Programming Society, La Jolla, 1993.
56. P. Moscato; An introduction to population approaches for optimization and hierarchical objective functions: A discussion on the role of tabu search. Annals of Operations Research, 41:85–121, 1993.
57. Bäck, Thomas & Hoffmeister, Frank & Schwefel, Hans-Paul; A Survey of Evolution Strategies., 2-9, 1991.
58. D.E. Goldberg; Genetic Algorithms in Search, Optimization, and Machine Learning. Addison-Wesley, Reading, 1989.
59. F. Glover; Heuristics for integer programming using surrogate constraints. Decision Sciences, 8:156–166, 1977.
60. J.H. Holland; Adaptation in Natural and Artificial Systems. The University of Michigan Press, Ann Arbor, 1975.