A Modified Elephant Herd Optimization Algorithm to Solve the Single Machine Scheduling Problems

M. K. Marichelvam, M. Geetha

***Abstract**: This study reports the single machine scheduling problem for finding the minimum the total weighted tardiness. As the problem is non-deterministic polynomial-time hard (NP-hard), the problem might not be answered by the exact solution techniques. Henceforth, different heuristics and meta-heuristics were recommended by different practitioners to tackle the problem. A modified elephant herd optimization algorithm (MEHOA) is investigated in the present work to solve the single machine total weighted tardiness scheduling problem (SMTWTSP). The performance of the anticipated approach is studied with the test instances available in the OR library. The outcomes are compared with several different algorithms offered in the literature and indicate the efficacy of the developed methodology.*

***Keywords**: scheduling, modified elephant herd optimization algorithm (MEHOA), single machine, NP-hard, tardiness.*

I. INTRODUCTION

Efficiency is perhaps one of the most crucial tasks in modern life and manufacturing environment. With scarce resources it's important to distribute these to right channels to gain competitive advantage. Effective utilization of resources plays a vital role for the growth of any organization as they own limited resources only. This is achieved by a technique called as scheduling. For the past several decades tremendous research works were carried out on different scheduling environment such as single machine, flow shop, parallel machine, job shop, flexible job shop, and hybrid flow shop, and so on. Among them, the single machine environment is the fundamental scheduling problem that was addressed by several investigators with a variety of objectives. The single machine scheduling environment entails of a single machine and n jobs. The important objectives considered in the literature are: minimization of makespan, flow time, tardiness, earliness, etc. Minimization of tardiness is one of the widely preferred scheduling objectives as it is associated with customer satisfaction which in turn may also improve the profit to the organization. Hence, weighted tardiness minimization is considered in this paper. As the single machine total weighted tardiness scheduling problem (SMTWTSP) is NP-hard (non-deterministic polynomial-time hard) [1-2] kind combinatorial optimization problem, exact solution techniques are impossible to find the best solution in a feasible time for this type of large scale problem instances. Researchers developed many heuristics and meta-heuristics for solving the NP-hard problems.

Most researchers tend to analyze the behaviors of living organism in their natural environment to developed different metaheuristic optimization algorithms. The elephant herd optimization algorithm (EHOA) is one of the newly introduced social algorithms [3]. The EHOA has been preferred by researchers to solve numerous optimization problems. Hence, the present work's aim is giving an efficient solution approach proposal to handle the SMTWTSP using a modified elephant herd optimization algorithm (MEHOA). The remaining of the paper is organized as given: Section II reviews the literature on single machine scheduling problems with weighted tardiness objective and the EHOA. Section III summarized the scheduling problem of the study. Section IV presents the developed solution technique. Section V describes the computational experiments. Finally, Section VI concludes the research along with some recommendations for future references.

II. LITERATURE REVIEW

A. Single machine total weighted tardiness scheduling problems

Scheduling problems are widely preferred in academic literature based on their real-life applications. Various test instances are selected to measure the efficiency of a newly developed metaheuristic and compare its performance against the previous known ones.

Several algorithms are developed in the literature for solving the SMTWTSP. Abdul-Razaq et al. [4] presented a comprehensive survey on the various methodologies proposed to solve the SMTWTSP until 1990s. Many researchers proposed Branch & Bound algorithm [5-7] to solve the SMTWTSP. Potts and Van Wassenhove [8] addressed several heuristics to solve the SMTWTSP. Huegler and Vasko [9] presented a detailed comparison of several heuristics for solving the SMTWTSP. Crauwels et al. [10] introduced different local search heuristics to solve the SMTWTSP. Akturk and Yildirim [11] suggested a dominance rule-based algorithm to solve the SMTWTSP.

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They evaluated the efficiency of the given method on 40000 random problem instances with 50, 100, 300 and 500 jobs and showed the significance of the proposed algorithm. Borgulya [12] developed a cluster-based evolutionary algorithm (CBEA) for solving the SMTWTSP. The CBEA consists of three stages. The local optimal solutions were grouped in the first stage and the accuracy of these solutions were further enhanced with the help of local search procedures in the second and third stages. Solution quality of the developed method is measured with the test instances from the OR library.

Congram et al. [13] established a new neighbourhood search technique, with the name of dynasearch to solve the SMTWTSP. In the proposed algorithm, dynamic programming is used for searching the exponential size neighbourhood in polynomial time. The efficiency of the developed approach was evaluated with the benchmark instances. Liu et al. [14] introduced a solution methodology using genetic algorithm (GA) to the SMTWTSP. The algorithm mimics the natural permutation presentation of a chromosome. The dispatching rules were used together with the random method to develop the initial population. The experimental solutions showed that the results found with the proposed GA were better than the integrated heuristic dispatching rules for performance comparison, but having needs of extra computation time. Ning et al. [15] introduced a new genetic algorithm to cope with the SMTWTSP. The proposed GA used the native permutation representation of a chromosome for the encoding strategy. Heuristic dispatching rules were used together with a random method to generate the initial solution. Position-based crossover and order-based mutation schemas were integrated to enhance the solution quality. The efficiency of the developed methodology was measured with the large size test problems. Ferrolho and Crisóstomo [16] applied a GA to solve the SMTWTSP. In their proposed approach, different crossover and mutation operators' performance are compared based on scheduling problems. Chou [17] suggested an experienced learning genetic algorithm (ELGA) solution method for the SMTWTSP. To further improve the solution quality, he also developed a lower bound-base bias roulette (LBBR) algorithm for generating the initial population. The efficiency of the developed solution technique is measured with the benchmark instances. Süer et al. [18] recommended a GA to solve the SMTWTSP.

Nearchou et al. [19] offered an improved simulated annealing methodology to the single machine scheduling problems. In the given solution method, dispatching rules are incorporated with the simulated annealing (SA) algorithm to enhance the solution efficiency. An approximation solution technique was introduced by Cheng [20] to solve the SMTWTSP. Arroyo et al. [21] addressed a Greedy Randomized Adaptive Search Procedure (GRASP) with path relinking for solving the SMTWTSP. A hybrid heuristic was combined with GRASP with Path Relinking to search for better quality solutions. The efficiency of the proposed approach was measured using the benchmark problems and solutions showed that the proposed methodology was very competitive. Kellegöz et al. [22] compared the performance of several genetic crossover operators for solving the SMTWTSP. The success of the given approach was measured with the test instances given in the literature. Maheswaran et al. [23] handled several hybrid heuristic algorithms for solving the SMTWTSP. The efficiency of the developed heuristics was evaluated using the benchmark instances.

Ant colony optimization (ACO) algorithm is another important algorithm suggested by several researchers to solve the SMTWTSP. It's based on the social information sharing principles of bees searching for the maximum nectar amount from the food sources. Bauer et al. [24] addressed the ACO algorithm to solve the SMTWTSP. They incorporated a modified due date (MDD) heuristic with the ACO algorithm to create better results. They carried out the performance measurement of the algorithm over the test problems from the OR library and showed the effectiveness of the ACO algorithm. Den Besten et al. [25] also used the ACO algorithm to solve the SMTWTSP. Holthaus and Rajendran [26] developed a fast ant-colony algorithm (FACO) for solving the SMTWTSP. In the FACO, the EDD dispatching rule and NEH heuristics were used to enhance the solution performance. The efficiency of the given approach was analyzed with the test instances. Merkle and Middendorf [27] also established an ACO for solving the SMTWTSP. In the proposed ACO, the places in the schedule are allocated in random order. Based on the algorithm proposed in the literature, Cheng et al. [28] introduced a hybrid algorithm. The proposed hybrid methodology was based on the ACO algorithm, and the elimination rules and the measurement of this new approach's performance using test instances showed the better performance of the proposed hybrid method over simple ACO algorithm. Madureira et al. [29] also suggested an ACO algorithm for solving the SMTWTSP. Efficiency of the proposed approach is measured with benchmark instances.

Nearchou et al. [30] introduced a hybrid metaheuristic algorithm (HMA) for finding efficient solutions to the SMTWTSP. Differential evolution (DE) and with variable neighbourhood search (VNS) are combined. The effectiveness of the HMA was measured with the test instances from the literature and solutions are seemed better than the comparing algorithms. Bożejko et al. [31] addressed a Tabu Search (TS) algorithm for handling the SMTWTSP. They proposed and evaluated some new features of the problem related with the blocks. Bilge et al. [32] developed a TS based solution approach for the SMTWTSP to obtain better solutions for a set of test instances addressed in the literature.

Parsopoulos and Vrahatis [33] developed a Unified Particle Swarm Optimization (UPSO) for solving the SMTWTSP. The performance was tested with the test instances given in the literature. Tasgetiren et al. [34] developed a particle swarm optimization (PSO) and differential evolution (DE) algorithms for solving SMTWTSP. They evaluated the efficiency of the given algorithms with the benchmark instances. Cagnina et al. [35] introduced an improved hybrid Particle Swarm Optimization (IHPSO) solution method to solve the SMTWTSP.

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Wang and Tang [36] combined VNS with TS to solve the SMTWTSP. Wang and Tang [37] also introduced a population-based variable neighbourhood search (VNS) for solving the SMTWTSP. Wang and Tang [38] applied a basic scatter search (SS) algorithm to achieve better solutions in the SMTWTSP. An investigation of local search neighbourhoods for solving the SMTWTSP was presented by Geiger [39]. El Majdouli and El Imrani [40] introduced a Discrete Fireworks algorithm (DFA) for solving the SMTWTSP. The proposed DFA is hybridized with VNS heuristic. The introduced approach is tested with several benchmark instances. A new VNS (NVNS) approach was proposed by Fu and Chung [41] for solving the SMTWTSP. Wang and Yin [42] presented a Differential evolution (DE) meta-heuristic with mixed strategy for solving the SMTWTSP. Yurtkuran and Emel [43] addressed a discrete artificial bee colony (DABC) algorithm for solving the SMTWTSP. An improved genetic simulated annealing algorithm (IGASA) was suggested by Chaabane [44] to solve the SMTWTSP. The genetic and simulated annealing algorithms were combined to obtain the advantages of both algorithms. The efficiency of the algorithm was measured with different test instances and compared with different metaheuristics.

A multiple-variable neighborhood search (MVNS) based solution technique was given by Chung et al. [45] for solving the SMTWTSP. The proposed algorithm's performance was measured with the well-known test instances. Ding et al. [46] developed a hybrid evolutionary approach (HEA) to handle the SMTWTSP. In this HEA, a dynasearch procedure is introduced for local searching. The improved dynasearch algorithm with the fast neighborhood search is also included. A buffer technique was included to the approach to decrease the computational time and a recombination operator and a population updating procedure were also used to further enhance the quality of the results. The solution quality of the given approach was evaluated with various test instances. Recently, Marichelvam and Geetha [47] presented a hybrid solution technique using cuckoo search algorithm for solving the SMTWTSP with sequence dependent setup times. They measured the efficiency of the given approach with different benchmark instances.

B. Elephant Heard Optimization Algorithm (EHOA)

Wang et al. [48] designed the EHOA for solving the global optimization tasks. Gupta et al. [49] suggested the EHOA to optimize the PID controller design. Ahmed et al. [50] suggested an improved Elephant Swarm Optimization Algorithm for community detection problem. The efficiency of the given algorithm was measured against many other well-known algorithms used in different studies and proved to be better. Alihodzic et al. [51] addressed the EHOA to handle the unmanned aerial vehicle path scheduling problem. The performance of the given approach was measured using parameters of the battlefield environments from the various previous studies and proved to be better. Kilany & Hassanien [52] hybridized the EHOA and support vector machines for the identification of human behaviour. Sambariya & Fagna [53] applied the EHOA for optimal design of PID controller for load frequency control in power system.

The EHOA was used to address the Home Energy Management System (HEMS) to minimize the electricity cost and waiting time [54-55]. The Acute lymphoblastic leukaemia cells were classified as normal or affected using the EHOA with neural networks by Sahlol et al. [56]. Tuba & Stanimirovic [57] addressed the EHOA for the parameter tuning of support vector machine. Tuba et al. [58] considered the multilevel image thresholding using the EHOA. Correia et al. [59] proposed the EHOA to tackle the energy-based source localization problem in wireless sensors networks. The key parameters of the EHOA were optimized using simulations. The efficiency of the EHOA was compared with the existing solutions and was proved to be more effective. The EHOA and cultural algorithm were hybridized to optimize the truss design problems by Jafari et al. [60]. The objective was to minimize the weight of the truss. The performance of the algorithm was evaluated for four problems.

Krishna & Ramanjaneyulu [61] handled wireless sensor networks problem and used EHOA based clustering and routing technique to find optimal placements. A multi objective distributed energy resource accommodation problem of distribution systems was tacked by Meena et al. [62] using an EHOA. Tuba et al. [63] introduced a chaotic EHOA (CEHOA) to solve the benchmark functions in the literature. Performance of the CEHOA was measured against the EHOA and PSO algorithms. The results indicated the better performance of the given CEHOA. Strumberger et al. [64] proposed the EHOA for optimal placement of drones. Recently, Elhosseini et al. [65] presented an improved EHOA to tackle the optimization problems. Ismaeel et al. [66] developed an enhanced version of EHOA for global optimization. Jaiprakash & Nanda [67] applied the EHOA for solving the clustering problems. The efficiency of the given method was measured with six benchmark problem instances. The results were compared with different well-known algorithms. Tuba et al. [68] solved the clustering problems by combining the EHOA and K-means. Though the EHOA is applied for wide variety of optimization problems, EHOA has previously never preferred for solving scheduling problems. For this reason, in this study, an attempt is made to handle the SMTWTSP using a modified EHOA (MEHOA).

III. PROBLEM DEFINIITON

The single machine total weighted tardiness scheduling problem (SMTWTSP) can be summarized as follows: A set of n jobs is to be operated without intervention on a single machine. The single machine can process only one job at a given time. The machine will be ready for the entire scheduling duration. The set-up time is negligible and is included in the processing time. All jobs are ready for handling at time zero. The processing time for job i is P_i and it is an integer. The due date and weight for the job i are d_i and w_i respectively. These values are also positive integers. The tardiness can be well-defined as the unpunctuality of a job if it is unavailable to meet its due date, or zero otherwise. Tardiness can be very important on a manufacturing environment but mostly related with the service quality and customer fulfilment [69]. The tardiness of job j is defined as:

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$$T_j = max(C_j - d_j, 0) \quad (1)$$

The objective of the study is finding the best schedule of the jobs that minimizes the total weighted tardiness given by

$$MinZ = \sum_{i=1}^{n} w_i T_j \quad (2)$$

IV. PROPOSED ALGORITHM

The main idea about EHOA is the social behaviors of the elephants. Elephants are one of the most important animals to maintain the bio-diversity of forests. A wide variety of elephants are living in the world. In general, these elephants live in a group like any other social animal. Each group is consisting of several clans. These clans may be considered as a family group. There is a matriarch in each clan which will lead the clan. A matriarch is known as the eldest female elephant in the clan. A clan is composed of one or more female elephants and their calves. The male elephants would like to live separately when they would have grown up. However, the male elephants can communicate with their clan using some low-frequency vibrations. The herding behavior of elephants are applied to solve the optimization problems by developing three rules [3]. The rules are given below:

1. Clans are the basic units of the elephant population. In each of this clan, the number of male and female elephants is fixed.
2. From the clan, a constant number of male elephants would leave.
3. The eldest female elephant is the matriarch of the clan and it will lead the clan.

In the EHOA, the population size (Npop) and the number of generation is defined first. A solution is represented by the position of an elephant. The population is divided into a fixed number of clans with a specific number of elephants in each clan. The position of the elephants is generated randomly. For each elephant, the objective function value is determined. An elephant with the better objective function value is considered as matriarch of the clan. The position of other elephants in the clan is updated using the clan operating operator that considers the position of the matriarch. An elephant with worst objective function would leave the clan. The separation operator is used for this purpose. Now, the elephant population is updated. For creating a new population, the above steps are repeated until the number of iterations are achieved.

A.Modified Elephant herd optimization algorithm (MEHOA)

In the MEHOA, some amendments are made.

1. Instead of randomly generating an initial population of elephants, a dispatching rule is preferred to create one of the initial solutions. This would be used to enhance the solution quality.
2. In the EHOA addressed in the literature, the mating behaviour of elephants were not considered. In the present work, the mating behaviour of male and female elephants is considered.
3. In the EHOA, it is possible that the solution to be trapped at local optima. To avoid this, a local search improving procedure is added to the basic MEHOA.

The steps in the MEHOA are presented below:

1. Define the parameters. The required parameters of the proposed approach are defined. Number of the elephants Npop, number of clans, number of elephants in each clan, the number of generations and the other basic variables are determined.
2. The position of Npop-1 elephants is generated randomly and the remaining one solution is generated using the earliest due date (EDD) dispatching rule [70].
3. The objective function value of each clan is calculated. The elephant with the better objective function value is considered as matriarch. The position of other elephants in the clan is also updated with respect to the position of the matriarch. The elephant with the worst objective function would leave the clan and this elephant is assumed to be a male elephant. Now, this male elephant would mate with one or more of the female elephants in the clan. The female elephants would be selected with a probability of Ps for mating. Then, a new clave will be generated. This process will be similar to the cross over operator in the GA [71]. Ischibuchi and Murata [72] suggested a two-point order-based crossover operator while solving the flow shop scheduling problems. This two-point order-based will generate only one offspring. This two-point order-based crossover operator is selected to generate a new clave.
4. The above step is repeated for all the clans in the elephant population and new claves are generated. This new clan may be either male or a female.
5. The above two steps are repeated until the stopping criterion is reached. The number of iterations is selected as the stopping criterion in this work. Hence, at the end of step 5, elephants with the best objective function values are identified for each clan. For these elephants, the local search algorithm is performed to prevent the solution to be trapped at the local optimum. The NVNS algorithm presented in [41] is used in this research.

V. COMPUTATIONAL RESULTS

In order to claim a new proposed solution technique's performance can be better than the other known approaches, benchmark problems can be used to effectively measure and compare its performance against the competitors. Therefore, different test problems are used to measure the efficiency of the modified solution idea and compared against other well-known solution methods. The population size and number of generations are selected as 100 in this study. The number of generations for the VNS is also fixed to 100.

A. Test problems

The performance of the given method is measured using test instances of SMTWTSP available in the OR library. 125 test problems are given for every problem size with different number of jobs (n) of 40, 50 and 100. The problems were randomly created. For each job, a processing time within the interval [1, 100], processing weight from the interval of [1, 10] are randomly created within the uniform distribution. For each test problem, different due dates were created by using uniform distributions separately for each control variable.

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For relative range of due dates (RDD) and average tardiness factor (TF) five value are taken. These values are (0.2, 0.4, 0.6, 0.8, 1.0) and using them an integer due date d_j for each job j was randomly created with [P (1-TF-RDD/2), P (1-TF+RDD/2)] within the uniform distribution. Where,

$$P = \sum_{j=1}^{n} P_j \quad (3)$$

There are total 25 variations of the RDD and TF pair. Each of this pairs, 5 different test problem is created. Thus, a total of 125 test instances for each value of n is exists. Each problem is repeated 10 times. The performance of the given MEHOA is measured against ACO [29], DABC [43], DE [42], GA [18], HSA [19], GRASP [21], and PSO [34] algorithms, widely used in similar studies. The parameters proposed in the respective papers are used in this paper to make a fair comparison. Relative Deviation Index (RDI) is used as the indicator of performance measurement to measure and evaluate the efficiency of selected methods. RDI is calculated for each problem instances by using the following equation:

$$RDI = \frac{Z_{Algorithms} - Z^*}{Z^*} \quad (4)$$

Where,

$Z_{Algorithms}$ – objective function value obtained by each of the selected solution approach

Z^* – Minimum objective function value

From the RDI values, Mean Relative Deviation Index (MRDI) is calculated as follows:

$$MRDI = \sum_{n=1}^{125} RDI \,/125 \quad (5)$$

The main performance evaluation of the selected metaheuristics are given in Table 1 using the MRDI indicator for each of the various problem size.

Table- I: MRDI comparison of different algorithms

Algorithms	MRDI		
	n=40	*n=50*	*n=100*
ACO [29]	1.03	1.08	1.12
DABC [43]	0.91	0.96	0.98
DE [42]	0.88	0.91	0.92
GA [18]	0.82	0.84	0.83
GRASP [21]	0.78	0.79	0.82
HSA [19]	0.72	0.75	0.77
PSO [34]	0.45	0.48	0.49
MEHOA	**0.05**	**0.06**	**0.05**

From the above table it is seen that the MRDI measurement for the MEHOA has the lowest value against other comparing algorithms. Lower MRDI value showed that the performance of the given methodology is better than other solution approaches. Main reason of having better solutions against other well-known metaheuristics can be due to the hybridization of the approach with the EDD rule and the VNS. The mean computational time (MCT) comparison of the selected algorithms is also carried out as shown in Table 2.

Table- II: Name of the Table that justify the values

Algorithms	MCT
ACO [29]	1.03
ACO [29]	5.32
DABC [43]	4.85
DE [42]	4.62
GA [18]	5.624
GRASP [21]	6.21
HSA [19]	4.25
PSO [34]	3.21

VI. CONCLUSIONS

In this study, a social algorithm utilizing the elephant's social life behaviors is proposed. A modified of the basic elephant herd optimization algorithm with different heuristics is given to elucidate the single machine weighted tardiness scheduling problem. As far as known, this paper is the first proposed study of the EHOA to solve the single machine total weighted tardiness scheduling problem. The well-known benchmark problems from the OR library are used to measure the solution quality of the developed methodology and the efficiency of the approach is evaluated against the best known results and other widely preferred algorithms. Solutions indicates that the given approach produced better quality solutions against the comparing algorithms. The proposed methodology is quite simple, and it reduces the time needed to find the optimal solution of the problem. There can be different future expansions to this methodology. The given approach based on several assumptions which are generally not realistic in real life manufacturing environment. Some of these assumptions could be lessened and the given solution strategy can be used to solve this new problem. The introduced solution methodology may be utilized to solve other type of scheduling problems with single and multi-objectives. Hybridization of the given methodology with different heuristics and dispatching rules would be another kind of future work.

REFERENCES

1. Lawler, E. L. (1977). A "pseudopolynomial" algorithm for sequencing jobs to minimize total tardiness. Annals of discrete Mathematics, 1, 331-342.
2. Lenstra, J. K., Kan, A. R., & Brucker, P. (1977). Complexity of machine scheduling problems. Annals of discrete mathematics, 1, 343-362.
3. Wang, G. G., Deb, S., & Coelho, L. D. S. (2015, December). Elephant herding optimization. In 2015 3rd International Symposium on Computational and Business Intelligence (ISCBI) (pp. 1-5). IEEE.
4. Abdul-Razaq, T. S., Potts, C. N., & Van Wassenhove, L. N. (1990). A survey of algorithms for the single machine total weighted tardiness scheduling problem. Discrete Applied Mathematics, 26(2-3), 235-253.
5. Babu, P., Peridy, L., & Pinson, E. (2004). A branch and bound algorithm to minimize total weighted tardiness on a single processor. Annals of Operations Research, 129(1-4), 33-46.

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6. Wodecki, M. (2008). A branch-and-bound parallel algorithm for single-machine total weighted tardiness problem. The International Journal of Advanced Manufacturing Technology, 37(9-10), 996-1004.
7. Zhou, S., & Liu, Z. (2013). A theoretical development for the total tardiness problem and its application in branch and bound algorithms. Computers & Operations Research, 40(1), 248-252.
8. Potts, C. N., & Van Wassenhove, L. N. (1991). Single machine tardiness sequencing heuristics. IIE transactions, 23(4), 346-354.
9. Huegler, P. A., & Vasko, F. J. (1997). A performance comparison of heuristics for the total weighted tardiness problem. Computers & Industrial Engineering, 32(4), 753-767.
10. Crauwels, H. A. J., Potts, C. N., & Van Wassenhove, L. N. (1998). Local search heuristics for the single machine total weighted tardiness scheduling problem. INFORMS Journal on computing, 10(3), 341-350.
11. Akturk, M. S., & Yildirim, M. B. (1999). A new dominance rule for the total weighted tardiness problem. Production Planning & Control, 10(2), 138-149.
12. Borgulya, I. (2002). A cluster-based evolutionary algorithm for the single machine total weighted tardiness-scheduling problem. Journal of computing and information technology, 10(3), 211-217.
13. Congram, R. K., Potts, C. N., & van de Velde, S. L. (2002). An iterated dynasearch algorithm for the single-machine total weighted tardiness scheduling problem. INFORMS Journal on Computing, 14(1), 52-67.
14. Liu, N., Abdelrahman, M. A., & Ramaswamy, S. (2003, March). A genetic algorithm for the single machine total weighted tardiness problem. In System Theory, 2003. Proceedings of the 35th Southeastern Symposium on (pp. 34-38). IEEE.
15. Ning, L. I. U., Abdelrahman, M., & Ramaswamy, S. (2005). A genetic algorithm for single machine total weighted tardiness scheduling problem. International journal of intelligent control and systems, 10(3), 218-225.
16. Ferrolho, A., & Crisóstomo, M. (2007, May). Single machine total weighted tardiness problem with genetic algorithms. In Computer Systems and Applications, 2007. AICCSA'07. IEEE/ACS International Conference on (pp. 1-8). IEEE.
17. Chou, F. D. (2009). An experienced learning genetic algorithm to solve the single machine total weighted tardiness scheduling problem. Expert Systems with Applications, 36(2), 3857-3865.
18. Süer, G. A., Yang, X., Alhawari, O. I., Santos, J., & Vazquez, R. (2012). A genetic algorithm approach for minimizing total tardiness in single machine scheduling. International Journal of Industrial Engineering and Management (IJIEM), 3(3), 163-171.
19. Nearchou, A. C. (2004, June). Solving the single machine total weighted tardiness scheduling problem using a hybrid simulated annealing algorithm. In Industrial Informatics, 2004. INDIN'04. 2004 2nd IEEE International Conference on (pp. 513-516). IEEE.
20. Cheng, T. E., Ng, C. T., Yuan, J. J., & Liu, Z. H. (2005). Single machine scheduling to minimize total weighted tardiness. European Journal of Operational Research, 165(2), 423-443.
21. Arroyo, J. E., Santos, A. G., Silva, F. L., & Araújo, A. F. (2008, September). A GRASP with path relinking for the single machine total weighted tardiness problem. In Hybrid Intelligent Systems, 2008. HIS'08. Eighth International Conference on (pp. 726-731). IEEE.
22. Kellegöz, T., Toklu, B., & Wilson, J. (2008). Comparing efficiencies of genetic crossover operators for one machine total weighted tardiness problem. Applied Mathematics and Computation, 199(2), 590-598.
23. Maheswaran, R., Ponnambalam, S. G., & Jawahar, N. (2008). Hybrid heuristic algorithms for single machine total weighted tardiness scheduling problems. International journal of intelligent systems technologies and applications, 4(1-2), 34-56.
24. Bauer, A., Bullnheimer, B., Hartl, R. F., & Strauss, C. (2000). Minimizing total tardiness on a single machine using ant colony optimization. Central European Journal of Operations Research, 8(2), 125-141.
25. Den Besten, M., Stützle, T., & Dorigo, M. (2000, September). Ant colony optimization for the total weighted tardiness problem. In International Conference on Parallel Problem Solving from Nature (pp. 611-620). Springer, Berlin, Heidelberg.
26. Holthaus, O., & Rajendran, C. (2005). A fast ant-colony algorithm for single-machine scheduling to minimize the sum of weighted tardiness of jobs. Journal of the Operational Research Society, 56(8), 947-953.
27. Merkle, D., & Middendorf, M. (2005). On solving permutation scheduling problems with ant colony optimization. International Journal of Systems Science, 36(5), 255-266.
28. Cheng, T. E., Lazarev, A. A., & Gafarov, E. R. (2009). A hybrid algorithm for the single-machine total tardiness problem. Computers & Operations Research, 36(2), 308-315.
29. Madureira, A., Falcao, D., & Pereira, I. (2012, November). Ant colony system based approach to single machine scheduling problems: weighted tardiness scheduling problem. In Nature and Biologically Inspired Computing (NaBIC), 2012 Fourth World Congress on (pp. 86-91). IEEE.
30. Nearchou, A. C. (2012). A hybrid metaheuristic for the single-machine total weighted tardiness problem. Cybernetics and Systems, 43(8), 651-668.
31. Bożejko, W., Grabowski, J., & Wodecki, M. (2006). Block approach—tabu search algorithm for single machine total weighted tardiness problem. Computers & Industrial Engineering, 50(1-2), 1-14.
32. Bilge, Ü., Kurtulan, M., & Kıraç, F. (2007). A tabu search algorithm for the single machine total weighted tardiness problem. European Journal of Operational Research, 176(3), 1423-1435.
33. Parsopoulos, K. E., & Vrahatis, M. N. (2006, December). Studying the performance of unified particle swarm optimization on the single machine total weighted tardiness problem. In Australasian Joint Conference on Artificial Intelligence (pp. 760-769). Springer, Berlin, Heidelberg.
34. Tasgetiren, M. F., Liang, Y. C., Sevkli, M., & Gencyilmaz, G. (2006). Particle swarm optimization and differential evolution for the single machine total weighted tardiness problem. International Journal of Production Research, 44(22), 4737-4754.
35. Cagnina, L., Esquivel, S., & Coello, C. A. C. (2007) Hybrid Particle Swarm Optimizers in the Single Machine Scheduling Problem. Studies in Computational Intelligence, Volume 49, 143-164.
36. Wang, X., & Tang, L. (2008, September). A Hybrid VNS with TS for the single machine scheduling problem to minimize the sum of weighted tardiness of jobs. In International Conference on Intelligent Computing (pp. 727-733). Springer, Berlin, Heidelberg.
37. Wang, X., & Tang, L. (2009). A population-based variable neighborhood search for the single machine total weighted tardiness problem. Computers & Operations Research, 36(6), 2105-2110.
38. Wang, X., & Tang, L. (2009, December). A simplified scatter search for a special single machine scheduling problem to minimize total weighted tardiness. In Decision and Control, 2009 held jointly with the 2009 28th Chinese Control Conference. CDC/CCC 2009. Proceedings of the 48th IEEE Conference on (pp. 6250-6255). IEEE.
39. Geiger, M. J. (2010). On heuristic search for the single machine total weighted tardiness problem–some theoretical insights and their empirical verification. European Journal of Operational Research, 207(3), 1235-1243.
40. El Majdouli, M. A., & El Imrani, A. A. (2016). Discrete Fireworks algorithm for single machine scheduling problems. International Journal of Applied Metaheuristic Computing, 7(3), 24-35.
41. Fu, Q., & Chung, T. P. (2016, December). A new approach for solving single machine total weighted tardiness (SMTWT) problem. In Industrial Engineering and Engineering Management (IEEM), 2016 IEEE International Conference on (pp. 438-441). IEEE.
42. Wang, J., & Yin, A. (2016). Differential evolution algorithm with mixed strategy for single machine total weighted tardiness problem. International Journal of Wireless and Mobile Computing, 11(4), 357-362.
43. Yurtkuran, A., & Emel, E. (2016). A discrete artificial bee colony algorithm for single machine scheduling problems. International Journal of Production Research, 54(22), 6860-6878.
44. Chaabane, L. (2017, December). A cooperative solver for single machine total weighted tardiness scheduling problem. In Embedded & Distributed Systems (EDiS), 2017 First International Conference on (pp. 1-5). IEEE.
45. Chung, T. P., Fu, Q., Liao, C. J., & Liu, Y. T. (2017). Multiple-variable neighbourhood search for the single-machine total weighted tardiness problem. Engineering Optimization, 49(7), 1133-1147.
46. Ding, J., Lü, Z., Cheng, T. C. E., & Xu, L. (2017). A hybrid evolutionary approach for the single-machine total weighted tardiness problem. Computers & Industrial Engineering, 108, 70-80.
47. Marichelvam, M. K. and Geetha, M. (2016). A hybrid cuckoo search metaheuristic algorithm for solving single machine total weighted tardiness scheduling problems with sequence dependent setup times. International Journal of Computational Complexity and Intelligent Algorithms, 1(1), 23–34.
48. Wang, G. G., Deb, S., Gao, X. Z., & Coelho, L. D. S. (2016). A new metaheuristic optimisation algorithm motivated by elephant herding behaviour. International Journal of Bio-Inspired Computation, 8(6), 394-409.

49. Gupta, S., Singh, V. P., Singh, S. P., Prakash, T., &Rathore, N. S. (2016). Elephant herding optimization based PID controller tuning. International Journal of Advanced Technology and Engineering Exploration, 3(24), 194.
50. Ahmed, K., Hassanien, A. E., & Ezzat, E. (2017). An efficient approach for community detection in complex social networks based on elephant swarm optimization algorithm. In Handbook of Research on Machine Learning Innovations and Trends (pp. 1062-1075). IGI Global.
51. Alihodzic, A., Tuba, E., Capor-Hrosik, R., Dolicanin, E., & Tuba, M. (2017, November). Unmanned aerial vehicle path planning problem by adjusted elephant herding optimization. In 2017 25th Telecommunication Forum (Telfor) (pp. 1-4). IEEE.
52. Kilany, M., & Hassanien, A. E. (2017, December). A hybrid elephant herding optimization and support vector machines for human behavior identification. In 2017 Eighth International Conference on Intelligent Computing and Information Systems (ICICIS) (pp. 178-184). IEEE.
53. Sambariya, D. K., & Fagna, R. (2017, July). A novel elephant herding optimization based PID controller design for Load frequency control in power system. In 2017 International Conference on Computer, Communications and Electronics (Comptelix) (pp. 595-600). IEEE.
54. Parvez, K., Aslam, S., Saba, A., Aimal, S., Amjad, Z., Asif, S., &Javaid, N. (2017, November). Scheduling of appliances in HEMS using elephant herding optimization and harmony search algorithm. In International Conference on Broadband and Wireless Computing, Communication and Applications (pp. 62-72). Springer, Cham.
55. Sarwar, M. A., Amin, B., Ayub, N., Faraz, S. H., Khan, S. U. R., & Javaid, N. (2017, August). Scheduling of appliances in home energy management system using elephant herding optimization and enhanced differential evolution. In International Conference on Intelligent Networking and Collaborative Systems (pp. 132-142). Springer, Cham.
56. Sahlol, A. T., Ismail, F. H., Abdeldaim, A., &Hassanien, A. E. (2017, December). Elephant herd optimization with neural networks: a case study on acute lymphoblastic leukemia diagnosis. In 2017 12th International Conference on Computer Engineering and Systems (ICCES) (pp. 657-662). IEEE.
57. Tuba, E., & Stanimirovic, Z. (2017, June). Elephant herding optimization algorithm for support vector machine parameters tuning. In 2017 9th International Conference on Electronics, Computers and Artificial Intelligence (ECAI) (pp. 1-4). IEEE.
58. Tuba, E., Alihodzic, A., & Tuba, M. (2017, June). Multilevel image thresholding using elephant herding optimization algorithm. In 2017 14th International Conference on Engineering of Modern Electric Systems (EMES) (pp. 240-243). IEEE.
59. Correia, S., Beko, M., da Silva Cruz, L., & Tomic, S. (2018). Elephant Herding Optimization for Energy-Based Localization. Sensors, 18(9), 2849.
60. Jafari, M., Salajegheh, E., & Salajegheh, J. (2018). An efficient hybrid of elephant herding optimization and cultural algorithm for optimal design of trusses. Engineering with Computers, 1-21.
61. Krishna, R. K., & Ramanjaneyulu, B. S. (2018). A EHO-Based Clustering and Routing Technique for Lifetime Enhancement of Wireless Sensor Networks. In Microelectronics, Electromagnetics and Telecommunications (pp. 391-399). Springer, Singapore.
62. Meena, N. K., Parashar, S., Swarnkar, A., Gupta, N., & Niazi, K. R. (2018). Improved elephant herding optimization for multiobjective DER accommodation in distribution systems. IEEE Transactions on Industrial Informatics, 14(3), 1029-1039.
63. Tuba, E., Capor-Hrosik, R., Alihodzic, A., Jovanovic, R., & Tuba, M. (2018, February). Chaotic elephant herding optimization algorithm. In 2018 IEEE 16th World Symposium on Applied Machine Intelligence and Informatics (SAMI) (pp. 000213-000216). IEEE.
64. Strumberger, I., Bacanin, N., Tomic, S., Beko, M., & Tuba, M. (2017, November). Static drone placement by elephant herding optimization algorithm. In 2017 25th Telecommunication Forum (Telfor) (pp. 1-4). IEEE.
65. Elhosseini, M. A., El Sehiemy, R. A., Rashwan, Y. I., & Gao, X. Z. (2019). On the performance improvement of elephant herding optimization algorithm. Knowledge-Based Systems, 166, 58-70.
66. Ismaeel, A. A., Elshaarawy, I. A., Houssein, E. H., Ismail, F. H., & Hassanien, A. E. (2019). Enhanced Elephant Herding Optimization for Global Optimization. IEEE Access, 7, 34738-34752.
67. Jaiprakash, K. P., & Nanda, S. J. (2019). Elephant Herding Algorithm for Clustering. In Recent Developments in Machine Learning and Data Analytics (pp. 317-325). Springer, Singapore.
68. Tuba, E., Dolicanin-Djekic, D., Jovanovic, R., Simian, D., & Tuba, M. (2019). Combined Elephant Herding Optimization Algorithm with K-means for Data Clustering. In Information and Communication Technology for Intelligent Systems (pp. 665-673). Springer, Singapore.
69. Marichelvam, M. K., Prabaharan, T., & Geetha, M. (2015). Firefly algorithm for flow shop optimization. In Recent Advances in Swarm Intelligence and Evolutionary Computation (pp. 225-243). Springer, Cham.
70. Baker, K.R. (1974) Introduction to Sequencing and Scheduling, 1st ed., John Wiley, New York.
71. Holland, J.H. (1975) Adaptation in Natural and Artificial Systems, University of Michigan Press, Ann Arbor.
72. Ischibuchi, H. and Murata, T. (1998). A multi-objective genetic local search algorithm and its applications to flow shop scheduling. IEEE Transactions on Systems, Man and Cybernetics, Vol. 28, No. 3, pp.392–403.

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