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An effective hybrid ant lion algorithm to minimize mean tardiness on permutation flow shop scheduling problem Dana Marsetiya Utama a,1,*, Dian Setiya Widodo b,2, Muhammad Faisal Ibrahim c,3, Shanty Kusuma Dewi a,4 a University of Muhammadiyah Malang, Malang, Indonesia b University of 17 Agustus 1945 Surabaya, Surabaya, Indonesia c Universitas Internasional Semen Indonesia, Gresik, Indonesia 1 dana@umm.ac.id; 2 diansetiyawidodo@yahoo.com; 3 faisalibrahim.ie@gmail.com; 4 shanty@umm.ac.id * corresponding author 1. Introduction Scheduling is the process of delegating tasks to a machine for accomplishment [1], and one of the challenges usually observed is the permutation flow shop problem (PFSP).

This is usually observed in the allocation of job sequencing through a machine, M, to achieve a particular performance. In a traditional PFSP, there is mostly idleness of machine during operations through the processing of just one task at a time, and it is directly ready. All the jobs have similar routing on every machine starting from M1 to M2, M3, M4, Mn [2][3], but one problem usually persistent is the minimization of the mean tardiness.

Therefore, appropriate scheduling is essential for companies to minimize this problem [4] posed due dates [5] and, consequently, increase customer confidence. Several factors are considered when conducting this process, and the major one is the differences in the penalties associated with the jobs, with the due date being the most prevalent [6]. Several experts have revealed that the PFSP case cannot be found in the polynomial time. Hence, it is included in NP-Hard problems [7]. Therefore, several attempts have been made by researchers to develop an algorithm to reduce tardiness.

Some have investigated the problem in a flow shop, for example, Kim [8], Fernandez-Viagas and Framinan [9] developed heuristic algorithms inspired by Nawaz et al. [10] while Nagano et al. [11] proposed a heuristics algorithm with no idleness. Moreover, a greedy A RTIC L E IN F O ABSTRACT Article history Received July 23, 2019 Revised December 15, 2019 Accepted February 22, 2020 Available online March 31, 2020 This article aimed to develop an improved Ant Lion algorithm. The objective function was to minimize the mean tardiness on the flow shop scheduling problem with a focus on the permutation flow shop problem (PFSP).

The Hybrid Ant Lion Optimization Algorithm (HALO) with local strategy was proposed, and from the total search of the agent, the NEH-EDD algorithm was applied. Moreover, the diversity of the nominee schedule was improved through the use of swap mutation, flip, and slide to determine the best solution in each iteration. Finally, the HALO was compared with some algorithms, while some numerical experiments were used to show the performances of the proposed algorithms.

It is important to note that comparative analysis has been previously conducted using the nine variations of the PFSSP problem, and the HALO obtained was compared to other algorithms based on numerical experiments. This is an open access article under the CC – BY-SA license. Keywords Optimization Mean tardiness Hybrid Ant Lion Flow shop Scheduling 24 International Journal of Advances in Intelligent Informatics ISSN 2442-6571 Vol. 6, No. 1, March 2020, pp. 23-35 Utama et al. (An effective hybrid ant lion algorithm to minimize mean tardiness …) algorithm was used by Karabulut [6], while Fernandez-Viagas and Framinan [12] developed a non- population-based algorithm.

Hallah [13] also proposed a hybrid heuristic model, while Kim et al. [14] suggested a new priority on flow shop scheduling. Despite the fact there are several kinds of literature on heuristics algorithm, NEH has been reported to perform effectively for PFSP cases [15]. Furthermore, several metaheuristics methods have been proposed such as the Genetic Algorithm (GA) [16], Tabu Search (TS) [17], Particle Swarm Optimizer (PSO) [18], and Simulated Annealing (SA) [19] while some of the new metaheuristics studied include hybrid discrete teaching-learning algorithm [20], Hybrid GA [21], Artificial Immune System, [22] and bi-population EDA [23].

Even though many methods have been proposed to reduce tardiness in PFSP, certain meta-heuristics have drawbacks such as a high computational time when solving large-scale problems and the production of optimal local solutions [24][25]. Recently, the focus of researchers has been on the use of nature algorithms to solve the optimization problem, and several alternative methods have been developed. For this

study, the Hybrid Ant Lion Optimization (HALO) algorithm was proposed to solve the PSFP by minimizing the mean tardiness.

ALO is an algorithm that mimics the behavior of the Ant Lion and the Ant to survive, and it was first introduced by Mirjalili [26]. It has been used to solve some scheduling problems such as the scheduling in the power system (Chopra and Mehta [27]), Hydro-Thermal Scheduling (Dubey et al. [28]), maintenance schedule (Umamaheswari et al. [29]) and minimizing makespan in the PFSP (Petric et al. [30]). This means one way to investigate the mean tardiness of PFSP is through the use of Hybrid Ant Lion Optimization (HALO).

Even though ALO has been reported to be used to solve some scheduling problems, no studies have been found to have used HALO on PFSP to determine the mean tardiness performance. Therefore, the objective of this research was to develop an effective Hybrid Ant Lion Optimization (HALO) to solve the mean tardiness in PFSP. This involved the provision of HALO with an improved NEH-EDD algorithm developed by Kim [8] as a search agent and the use of computational experiments for analysis.

These were conducted to establish a comparison with several other algorithms in previous literature. This study contributes to the body of knowledge by 1) developing a new HALO algorithm to solve PFSP using mean tardiness performance, 2) determining the best parameters of the HALO algorithm, 3) discovering the computational time and efficiency of the HALO algorithm compared to previous ones.

Therefore, the Part 2 of this paper explains the assumption and description of problems, formulation of problems, proposed algorithm, data generated, and experimental procedure, Part 3 presents experimental parameters and benchmarking algorithms while the inference is presented in Part 4. 2. Method 2.1. Problem assumption and description The assumptions made in the problem are (1) sequencing involves the collection of n tasks which are ready at time 0, (2) each job has processing times for each process, (3) the time available for resources or machines is 0, (4) the set-up time is zero and covered by the processing time, (5) jobs are independent of each other, (6) interrupt is not allowed on every job, (7) each job has a fixed due date, (8) the machine only processes one job at a time, and (9) the processing time for every job on each machine is deterministic. Table 1 provides an example of the problem for three machines and three jobs while Fig.

1 shows the completion time of each job if the sequences J1, J3, and J2 are 6, 9, and 11 in (a) and if J2, J3, and J1 are 6, 9, and 11 respectively in (b). Even though the two schedules have the same time of completion, sequence (b) had the best result for the

mean tardiness with a value of 0 while (a) had 1.65 hours with a due date of 11,9 and 6. This means (a) has 5-hour tardiness while (b) has none. 25 Vol. 6, No. 1, March 2020, pp. 23-35 U al. (ftiybion algi mimie mean tarnes...) Table 1.

Time of process, ???? at every machine (hour) jobs Machines dj M1 M2 M3 J1 3 2 1 11 J2 3 1 2 6 J3 2 1 3 9 Fig. 1. The difference of 2 sequences The aim was to minimize mean tardiness, and the notation used throughout this paper is shown in Table 2. Table 2. The notation used throughout this paper Variable Definition Jobs Index Machine index, Total number of jobs Total number of machines ???? , ?? Processing time of job sequence i on machines Completion time of job sequence on machines Completion time job Tardiness for a job Mean tardiness Total lateness.

Therefore, using these notations, the following formulas were developed from the PFSP problem: (1) , (2) , (3) , , (4) , (5) (6) (7) 26 Utama et al. (An effective hybrid ant lion algorithm to minimize mean tardiness ...) $?? = ? ?? ?? ?? ?? = 1 ? ?$ (9) The best permutations are defined as the ones with minimal mean tardiness. Therefore, the PFSP model to minimize tardiness is as follows: O fuo Z = m ? ?? ?? ?? ?? = 1) / ?? ? ? ? ? ? ? Subject to: ?? 1 , 1 = ?? 1 , 1 ? ? ?? 1 , ?? = ?? 1 , ?? - 1 + ?? 1 , ?? ? ? ? ?? = 2 . .

?? ? ? ? ?? ?? , 1 = ?? ?? - 1 , 1 + ?? ?? - 1 , 1 ? ? ? ?? = 2 . . ?? ? ? ? ?? ?? , ?? = ???? (?? ?? - 1 , ?? , ?? ?? , ?? - 1) + ?? ?? , ?? ? ? ? ?? = 2 . . ?? ? ? ?? = 2 . . ?? ? ? ? ? ? ? ? Equation (1) describes the completion time of sequence 1 on machine 1, Equation (2) on the completion time of sequence 1 on machines 2 to m, and Equation (3) on the completion time of Sequence i on the machine 1. Moreover, Equation (4) shows the completion time of sequence i on machines j, Equation (5) presents the completion time job , Equation (6) shows the tardiness of the job , Equation (7) shows the mean tardiness of the permutation, and Equation (8) describes the lateness job i.

Furthermore, Equation (9) describes the total lateness of the permutation, Equation (10) explains the objective function of the PFSP model to minimize mean tardiness, and Equation (11) defines the constraint of the mean tardiness of the model. However, the constraints of the model are equations (1) to (6). 2.2. The Proposed Hybrid Ant Lion Algorithm (HALO) The Hybrid Ant Lion Algorithm (HALO), which mimics the survival behavior of Lion and Ant, was proposed. This was an advancement to the research conducted by Mirjalili [26], which proposed the Ant Lion Algorithm (ALO) to solve the problem of continuous optimization without the function to complete the PFSP.

This method made use of local search strategies such as swaps, flips, and slides and with the insertion of the NEH algorithm (Algorithm 1) to replace a one search agent to solve the PFSP problem. HALO consisted of five steps which include initializing the search agent position, converting the position to Large Rank Value (LRV) job permutation, changing the position of one search agent using NEH, updating the position of the search agent, and performing a local swap search, flip, and slide search. Moreover, the HALO pseudo-code was shown in Algorithm 2. The five steps are, however, discussed in the following sections. 2.2.1.

Initialization of the search agent positions The initial location of the search agent was randomly generated and configured to avoid no loop numbers in similar agents [15], as shown in Fig. 2. The matrix shows the number of search agents in the row and the dimensions in the column based on the number of jobs. However, Fig. 2 shows the matrix with 2 rejected position has the same random number for search agent 1 with 0.81 and search agent 2 with 0.43. Therefore, it cannot be used for scheduling. (1) Accepted position (2) Rejected position [0 . Fig. 2. Initialization of the positions of the search agent Ant position is presented with a matrix (Equation (12)).

U al. (ftiybion algi mimie mean tarnes...) ?? ???? = (12) The position Ant matrix was represented by . For , indicates the -th Ant vector while is the number of Ants. Moreover, the fitness function of the Ant was used as the matrix based on (13). ???? = (13) describes the position matrix for the Ant Lion according to (14) while the fitness function is represented by the matrix ?? OAL based (15).

?? Ant L = (14) = (15) For the , indicates the - is the number of Ant Lions while is the objective function. 2.2.2. The NEH-EDD algorithm This study made use of a new NEH-EDD algorithm as a search agent, and simple NEH usually involves setting the number of processing times for each job from the largest to the smallest [10]. However, in Kim [8] NEH-EDD algorithm, the work sequence was based on the smallest due date to the largest and was calculated to have the best mean tardiness.

Therefore, a new NEH-EDD algorithm was proposed to minimize mean tardiness differently from the NEH. This involves sorting the jobs by the smallest due date followed by the evaluation of the subsequences by the mean tardiness and total lateness as shown in Algorithm 1 (Fig. 3). Algorithm 1. Proposed NEH-EDD Procedure 1. Input: S = tasks arranged in the increase order of , where dj = d1 d2 dj 2.

Select the partial sequence with the smallest mean tardiness using Equation (8) into the partial sequence of ties between s = (S[1], S[2]) or s = (S[2], S[1]), and if the mean

tardiness is the same, the partial sequence with the minimum total lateness using (9) should be selected. 3. for k = 3 to n do 4. Investigate the insertion of S[k] in every feasible place in s from 1 to k + 1 in the partial sequence . 5. Select the best insertion, for instance, the insertion with the smallest mean tardiness using (7) and if the mean tardiness is the same, select the partial sequence with the minimum total lateness calculated from (9). 6. end for 7. return (s) Fig. 3.

Proposed NEH-EDD Procedure algorithm. 28 International Journal of Advances in Intelligent Informatics ISSN 2442-6571 Vol. 6, No. 1, March 2020, pp. 23-35 Utama et al. (An effective hybrid ant lion algorithm to minimize mean tardiness ...) 2.2.3. Apply Large Rank Value (LRV) to convert search agents to job permutations The use of Large Rank Value (LRV) was proposed for the conversion of search agents to job permutations. LRV is an effective method to map continuous values into job permutations by ranking the values from the largest to the smallest [31]. Fig. 4(a) shows the incorrect job permutations generated due to the PFSP condition, and Fig.

4 (b) is also not correct because it has the same position as the value. Therefore, the first job is in two different types. 0.12 0.29 0.11 0.81 J1 J2 J3 J4 3 2 4 1 (a) Correct Job Permutation (b) Incorrect Job Permutation Fig. 4. Large Rank Value Representation 2.2.4. Update Position of Ant Lion Algorithm (ALO) Ant's Lion was allowed to hunt other Ants down when moving around looking for food. This concept is, therefore, modeled in (16). X (t) = [0 , ?????? (2 ?? (?? 1) - 1) , ?????? (2 ?? (?? 2) - 1) , ... , ?????? (2 ?? (?? ??) - 1] (16) Cumsum is a calculation of ???? , is the maximum number of iterations, and indicates the -iteration.

Moreover, was formulated as a stochastic function in (17). ?? (??) = { 1 , (17) The Ant Lion moves in a random position in each step, and Equation (18) was used to ensure the Ant remains within the search range [21]. = (?? ?? ?? - ?? ??) ?? (?? ?? - ?? ?? ??) (?? ?? ?? - ?? ??) + ?? ?? , (18) Where ?? ?? is the minimum random walk of a ?? - ?? h variable, ?? ?? is the maximum random walk in the ?? variable, ?? ?? ?? shows the maximum ?? variable in the iteration ?? - ?? h , and ?? ?? ?? is the minimum ?? variable in the ?? - ?? h iteration. Moreover, the traps on the Ant Lion were modeled, as shown in the (19).

?? ?? ?? = ?????????? ?? ?? + ?? ?? , = ???????? ?? ?? + ?? ?? (19) Where is the minimum of all variables in the iteration, indicates the vector of the maximum variables in the iteration, is the minimum of all variables for the Ant, is the maximum of all variables for Ants , and shows the position of the Ant Lion selected at the iteration. Furthermore, the shift of the Ants to the directions of the Ant Lion was modeled on (20) to produce = ?? ?? ?? , ?? ?? = ?? ?? ?? , ?? = . (20) 0.12 0.29 0.11 0.11 J1 J2 J3 J4 2 3 1 1 Apply LRV Apply LRV ISSN 2442-6571 International Journal of Advances in Intelligent Informatics 29 Vol.

(ftiybion algi mimie mean tarnes...) Each Ant runs randomly around the Ant Lion chosen by the roulette wheel, and the position of the Ant Lion was selected in the Iteration using (21). = ?? ?? (21) Where describes the position of the Ant Lion selected in iteration, shows a random walk around the Ant Lion selected from the roulette wheel in the iteration, and describes a random walk around the elite in iteration. In the ALO algorithm, the Ant Lion changes its position to the hunted position if Ant has better fitness, and this is represented in (22). ???????? ?? = if ????) (22) 2.2.5.

The local search The local search is a combinatorial method applied to optimize the initial sequence up to when the optimum objective function is obtained [32], and the best solution is produced. Effective metaheuristic algorithms generally apply to local search [33], and the proposed steps include swap, flip, and slide. Do swap was conducted by randomly exchanging two job sequences, and the transactions in the iterations to t were repeated as as illustrated in Fig. 5.

The Do Flip rule was to reverse the order of the selected jobs, and the operation in iterations to t was repeated as as illustrated in Fig. 6. Moreover, Do Slides were conducted by shifting the job sequence and the operation in the iteration t was also repeated as much as as shown in Fig. 7. However, they are not allowed to be repeated in one iteration in the proposed local search. Fig. 5. Do Swap Illustration Fig. 6. Do Flip Illustration Fig. 7. Do Slide Illustration 2.3. The data generation and experimental procedure Several experiments were randomly conducted to evaluate the proposed HALO algorithm (Fig.

8) through the use of data from the number of jobs, the number of phases (machines), time of operation, and the due date. The experiments were conducted in three-set groups include small (5, 12 and 19), moderate (26, 30 and 50), and large (75, 100, and 200), and this led to the difference of 9 in the overall number of jobs. For the purpose of this study, four different jobs, comprising of 5, 7, 10, and 20, were used with three variations of machines in each group.

Moreover, processing time was generated by a uniform distribution of 12, 497 in minutes units while the due date for each job was randomly generated with a uniform distribution of 2100, 5040 in minutes. Experiments were also conducted with a combination of different parameters in the HALO algorithm through the use of variables of population and iteration. However, the population analysis made use of 2 levels, including 5 and 20, while the iterative experimental parameters used 9 levels, including 10, 15, 20, 25, 30, 35, 40, 45, and 50.

It is also important to state that 162 experiments were conducted covering each group to ensure the best parameters of the HALO algorithm. 30 International Journal of Advances in Intelligent Informatics ISSN 2442-6571 Vol. 6, No. 1, March 2020, pp. 23-35 Utama et al. (An effective hybrid ant lion algorithm to minimize mean tardiness ...) Algorithm 2. Proposed Hybrid Ant Lion Algorithm Input: a set Job, the due date, iteration maximum, population. Randomly initialize th?rst pultiof Ants and Ant Lions Apply LRV on each search agent to be mapped into job permutation Solve the PFSSP using NEH Choose one search agents from the population and replace it with NEH Ants and Ant Lions using Equation (8) Find the best Ant Lions and assume it as the elite or determined optimum W* = The best search agent t=0 while (t < iteration) for every Ant (population) Select an Ant Lion using a Roulette wheel Update c and d using (20) Create a random walk and normalize it using (16) and (18) Update the position of Ant using (21) end for Apply LRV on each search agent to be mapped into job permutation Ants using (8) Replace an Ant Lion with its corresponding Ant if using (22) ?? ?? = ?tiiatit Update the elite if an Ant Lion becom?tth it. If End if Apply Local search For i = 1: Perform swap on the . Ensure no repeated swap in the If End if End for For j = 1: Perform flip on the . Ensure no repeated swap in the If End if End for For k = 1: Perform slide on the .

Ensure no repeated swap in the If End if End for end while Return elite Fig. 8. Proposed Hybrid Ant Lion Algorithm Furthermore, to investigate the effectiveness of the HALO, its best algorithm parameters were compared with several previous algorithms such as Kim [8], Vallada and Ruiz [16], Parthasarathy and Rajendran [34], Nagano et al. [11], and ALO [30]. Moreover, the computational experiments were written in MATLAB R16 software for Windows 8.1 AMD x86-64 RAM 4 GB. The performance was measured using the Efficiency Index Percentage (EIP) and Relative Error Percentage (REP).

The EIP was identified as the mean tardiness ratio between the HALO and another percentage algorithm in (21), ISSN 2442-6571 International Journal of Advances in Intelligent Informatics 31 Vol. 6, No. 1, March 2020, pp. 23-35 U al. (ftiybion algi mimie mean tarnes...) and HALO was considered more powerful If EIP < 100 percent, the same if it is equal to 100%, and less powerful if EIP > 100 percent. The REP was also tested with another algorithm using (22). (21) (22) 3. Results and Discussion 3.1 Experimental parameters of the Hybrid Ant Lion Optimization The result of the simulated parameters of HALO is shown in Table 3, and it was discovered that a higher number of iterations and population led to lower mean tardiness.

This is in accordance with the claims of Haddock and Mittenthal [24]. Furthermore, the computational time simulation parameters were shown in Table 4, and the results

showed a higher number of iterations and populations produced significant computational time, which further led to a better selection of a solution. Moreover, a higher number of jobs was found to require more time. Therefore, the PFSP was included in the NP-Hard problems in line with the result of the research conducted by Utama et al. [7] and Garey et al. [35]. Table 3.

Comparison of each parameter towards efficient mean tardiness Iteration Job Family n x m Population 10 15 20 25 30 35 40 45 50 5 Small 5 x 5 0 0 0 0 0 0 0 0 0 0 12 x 7 798 757 704 667 663 661 650 638 632 19 x 10 1801 1584 1544 1442 1431 1393 1369 1340 1329 Medium 26 x 20 2362 2251 2239 2204 2162 2156 2113 2098 2097 30 x 5 2669 2579 2533 2436 2423 2389 2389 2372 2336 50 x 10 5111 5099 5090 5080 5030 5004 4969 4913 4869 High 75 x 20 8417 8349 8293 8281 8225 8215 8175 8166 8053 100 x 5 11546 11499 11483 11473 11469 11416 11317 11294 11234 200 x 10 23848 23683 23559 23445 23265 23262 23206 23171 23134 20 Small 5 x 5 0 0 0 0 0 0 0 0 0 0 12 x 7 716 648 641 639 629 628 617 610 610 19 x 10 1499 1429 1417 1379 1371 1362 1336 1305 1289 Medium 26 x 20 1381 1378 1372 1294 1270 1262 1240 1206 1162 30 x 5 2331 2325 2169 2156 2145 2107 2007 1999 1950 50 x 10 5115 4918 4862 4822 4743 4736 4679 4673 4610 High 75 x 20 7950 7817 7806 7615 7424 7376 7375 7365 7313 100 x 5 10922 10898 10883 10785 10773 10769 10682 10609 10549 200 x 10 23904 23667 23453 23374 23257 22982 22945 22899 22690 32 International Journal of Advances in Intelligent Informatics ISSN 2442-6571 Vol. 6, No. 1, March 2020, pp. 23-35 Utama et al.

(An effective hybrid ant lion algorithm to minimize mean tardiness ...) Table 4. Comparison of each parameter towards computational time Iteration Job Family n x m Population 10 15 20 25 30 35 40 45 50 5 Small 5 x 5 0.000 0.016 0.016 0.031 0.031 0.031 0.031 0.031 0.047 12 x 7 0.000 0.016 0.027 0.031 0.047 0.047 0.063 0.063 0.094 19 x 10 0.047 0.063 0.063 0.063 0.078 0.094 0.094 0.109 0.125 Medium 26 x 20 0.094 0.109 0.109 0.141 0.172 0.203 0.203 0.234 0.266 30 x 5 0.218 0.218 0.219 0.234 0.250 0.266 0.266 0.281 0.313 50 x 10 0.594 0.672 0.672 0.672 0.703 0.719 0.750 0.750 1.156 High 75 x 20 1.875 1.922 1.969 1.984 2.016 2.109 2.125 2.188 2.234 100 x 5 4.547 4.703 4.734 4.766 4.781 4.828 4.984 5.031 5.250 200 x10 43.54 43.547 43.750 43.813 43.82 43.98 44.094 44.17 44.34 20 Small 5 x 5 0.000 0.047 0.034 0.085 0.085 0.066 0.088 0.069 0.103 12 x 7 0.000 0.047 0.065 0.081 0.127 0.094 0.175 0.156 0.272 19 x 10 0.113 0.169 0.125 0.175 0.187 0.253 0.253 0.252 0.325 Medium 26 x 20 0.281 0.306 0.328 0.380 0.378 0.528 0.609 0.609 0.770 30 x 5 0.502 0.546 0.635 0.656 0.675 0.691 0.531 0.563 0.844 50 x 10 1.188 1.344 1.949 1.478 1.687 1.438 1.650 1.875 3.006 High 75 x 20 3.750 5.766 4.725 4.167 4.636 4.852 6.163 5.031 4.916 100 x 5 12.27 10.347 10.416 12.391 11.47 11.10 12.46 11.57 12.600 200 x10 87.23 121.93 131.25 131.43 92.03 92.36 110.23 88.34 124.16 3.2

Results Comparison Algorithms As previously stated, the HALO was compared with

several algorithms, and it was discovered that while the number of cases was increasing, a better result of mean tardiness was recorded <mark>as shown in Table</mark> 5. It also showed HALO needed a large computational time for each case study to produce better solutions. Table 5. The comparison of mean tardiness and computational time (in second) Job Family n x m HALO NEH-EDD [8] Nagano et al. [11] GA [16] SA [34] ALO [30] Mean Tardiness Time Mean Tardiness Time Mean Tardiness Time Mean Tardiness Time Mean Tardiness Time Mean Tardiness Time Small 5 x 5 0 0.103 0 0.000 0 0.000 0 0.104 0 0.047 0 0.000 12 x 7 609 0.272 726 0.012 639 0.083 673 0.154 649 0.094 700 0.083 19 x 10 1289 0.325 1568 0.125 1405 0.119 1386 0.113 1382 0.125 1477 0.119 Medium 26 x 20 1162 0.770 2252 0.294 1295 0.288 1301 0.281 2113 0.266 1777 0.288 30 x 5 1950 0.844 2579 0.318 2117 0.410 2171 0.502 2399 0.313 2375 0.410 50 x 10 4610 3.006 5131 0.594 4777 0.891 4758 1.188 4933 1.156 4945 0.891 High 75 x 20 7313 4.916 8309 1.875 7415 2.813 7468 3.750 8206 2.234 7889 2.813 100 x 5 10549 12.600 11525 4.547 10812 8.412 10795 12.277 11306 5.250 11160 8.412 200 x 10 22690 124.163 23581 43.542 23005 65.388 23275 87.234 23208 44.344 23428 65.388 Table 6 shows the comparison between the Relative Error Percentage (REP) and Efficiency Index Percentage (EIP) of the HALO and several algorithms.

Job family including small, medium, and large sizes was used for evaluation. The result showed the REP of HALO was stronger than other algorithms, such as NEH-EDD [8] with 23%, Nagano et al. [11] with 5%, Genetic Algorithm [16] 6%, Simulated Annealing 16%, and ALO 10%. It was also discovered that as the number of cases increased, the HALO provided better performance over the other four algorithms. Moreover, the Efficiency Index Percentage (EIP) revealed the increment in the number of cases led to the provision of more significant performance for the HALO algorithm. The values of EIP of mean tardiness for NEH-EDD [8], Nagano et al.

[11], <mark>ISSN 2442-6571 International Journal of Advances in Intelligent Informatics 33</mark> Vol. 6, No. 1, March 2020, pp. 23-35 U al. (ftiybion algi mimie mean tarnes...) Genetic [16], Simulated Annealing, and ALO were found to be 23%, 84%, 96%, 95%, and 89% respectively. Therefore, all the numerical experiments conducted showed HALO algorithm performs better. Table 6. Comparison of Relative Error Percentage (REP) and Efficiency Index Percentage (EIP) Job Family n x m NEH-EDD [8] Nagano et al.

[11] GA [16] SA [34] ALO [30] EIP REP EIP REP EIP REP EIP REP EIP REP Small 5 x 5 100% 0% 100% 0% 100% 0% 100% 0% 100% 0% 12 x 7 84% 19% 95% 5% 90% 11% 87% 7% 87% 12% 19 x 10 82% 22% 92% 9% 93% 8% 87% 7% 87% 12% Medium 26 x 20 52% 94% 90% 11% 89% 12% 65% 82% 65% 27% 30 x 5 76% 32% 92% 9% 90% 11% 82% 23% 82% 16% 50 x 10 90% 11% 97% 4% 97% 3% 93% 7% 93% 7% High 75 x 20 88% 14% 99% 1% 98% 2% 93% 12% 93% 7% 100 x 5 92% 9% 98% 2% 98% 2% 95% 7% 95% 5%

200 x 10 96% 4% 99% 1% 97% 3% 97% 2% 97% 3% 4. Conclusion The problem of permutation flow shop scheduling was studied to minimize mean tardiness through the use of Hybrid Anti-Lion Optimization (HALO) algorithms, and the performance was compared with several other algorithms.

The result of the computational experiments conducted showed the Hybrid Ant-Lion optimization algorithm achieved optimum mean tardiness. It is recommended that this approach is used as an initial solution for different metaheuristic algorithms and also in reducing the mean tardiness in more complicated permutation flow shop scheduling problems. Acknowledgment The authors appreciate the Directorate of Research at the University of Muhammadiyah Malang for the support provided for the research as well as the Department of Industrial Engineering Optimization Laboratory for the use of their facilities.

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