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The hybrid whale optimization algorithm: A new metaheuristic algorithm for energy-efficient on flow shop with dependent sequence setup

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Abstract. Recently, The industrial sector produces about half of the worlds total energy consumption. Manufacturing companies are required to reduce energy consumption. This article aims to develop a Hybrid Whale Optimization Algorithm (HWOA). We use the objective function of minimizing energy consumption. It solves the problem with permutation flow scheduling problems (PFSSP). Dependent sequence setup is a PFSSP problem with setups that depend on schedule sequence. We offer HWOA with local search strategies. The solution in each HWOA iteration is improved using flip and swap mutations. Furthermore, HWOA is compared with several algorithms. We use numerical experiments to show the performance of the proposed algorithm. Comparative analysis with several algorithms has previously been carried out with ten variations of PFSSP problems. Based on numerical experiments, HWOA proved to be competitive compared to other algorithms.
Keywords; Efficient; Energy; Flow shop; HWOA

1. Introduction

Recently, fossil fuels dominate the company's energy supply [1]. The industrial sector produces about half of the world's total energy consumption [2]. Therefore, manufacturing companies are the primary source of global warming. Manufacturing companies are required to reduce energy consumption [3]. Generally, energy consumption occurs during the production process. However, for the most part, energy is consumed when the engine is idle[4]. This issue has caught the attention of researchers in the field of scheduling. Scheduling is the allocation of limited resources to be managed efficiently [5]. Generally, Scheduling has the performance to minimize completion time. However, at present, it uses the performance of minimizing energy consumption [6]. Energy consumption has a vital role in the problem of global warming [5]. Emissions are caused by the burning of fossil fuels [3].
The problem of idle engine energy consumption can be solved by the ON-OFF strategy [4]. However, not all industries can apply the ON-OFF strategy [7]. Therefore, the right scheduling can minimize energy consumption. One of the problems in minimizing energy consumption is the case of the permutation flow shop scheduling problem (PFSSP). It has n jobs in the same order [8]. Some

researchers have researched scheduling to minimize energy consumption. Some algorithms used include Genetic Algorithm [9], Hybrid Genetic Algorithm [10], hybrid multi-objective backtracking search algorithm [11], Particle Swarm Optimization (PSO) [12], Heuristics [13] and Cross-Entropy Genetic Algorithm [14]. Based on previous research, at present, the metaheuristic algorithm is interesting to study [15]. Some experts claim the PFSSP case cannot be resolved in polynomial time. Thus, PFSSP is included in the NP-Hard problem [14] [16]. Therefore a new approach is needed to minimize energy consumption.

As far as we know, no previous research has investigated energy consumption minimization using the Hybrid Whale Optimization Algorithm (HWOA) algorithm. Whale Optimization Algorithm is a new metaheuristic algorithm that mimics the behavior of prey whales hunting [17]. We offer an approach to overcome the problem of minimizing energy consumption using the HWOA algorithm. In this study, HWOA is used for scheduling with the machine set up time depending on the sequence of job. In this case, we also consider the removal time. Therefore, the purpose of this study is twofold: First, to develop the WOA algorithm (HWOA) to minimize energy consumption in PFSSP. Second, this study knows the best parameters of the HWOA algorithm. The proposed main contribution in this field is to propose a new HWOA algorithm and propose the best parameters to solve minimizing the energy consumption.

2. Methods

2.1 Assumptions Problems and notations

Assumptions in flow shop scheduling with dependent set up time and removal time; (1) the sequence of jobs ($n = 1,2,3,\ldots,j$) carried out on m machines ($m = 1,2,3,\ldots,i$) is the same. (2) All machines are available on t = 0. (3) set up time is dependent on the order of work. (4) set up time is separate from processing time. (5) set up a time for moving from job j to job k on the machine i is S (where $j = k$, Sij indicates the setup time for job j if the job is the first job in sequence). (6) the removal time is separate from the processing time. (7) each job when it starts processing to finish should not be interrupted. (8) Each machine starts at time = 0 and finishes when the last job on each machine is finished (each machine that stops independently of the other machines). The purpose of this model is to minimize total energy consumption (TEC). The notation in the total energy consumption used in this article is as follows:

i	:	index of jobs, $i = 1,2 \ldots, n$
j	:	index of machines, $j = 1,2 \ldots, m$
n	:	total number of jobs
m	:	total number of machines
$P\ ,j$	:	processing time of job sequence i on machines j
S	:	Setup time of job i in the first sequence on every machine
$S_{i-1,i}$	:	set up time move sequence $i-1$ to i on machine
$R\ ,j$	:	waktu removal untuk job i pada mesin j
$R\ j$	:	energy consumption index of machine j when removal
$P\ j$	:	energy consumption index of machine j
$S\ j$	:	energy consumption Setup index of machine j
$I\ j$	:	energy consumption index of machine j when idle
$C\ ,j$	:	completion time of job sequence i at on machines j
T	:	completion time of machines j
Bj	:	total busy time of machines j
Ij	:	total idle time of machines j
Sj	:	total setup time of machines j
Rj	:	Removal time of machines j
T	:	total energy consumption
$\vec{D}$	:	the initial distance of the whale to it is prey
$\overrightarrow{D'}$	:	the distance of whales to prey (from the best solution)
$\vec{X}$	:	vector position
$\overrightarrow{X^*}$	:	vector position of the best solution
$\vec{A}$	:	vector coefficient
$\vec{C}$	:	vector coefficient
t	:	number of iterations
b	:	a constant to define a spiral shape
l	:	random numbers with ranges [-1,1]

Based on the above notation, the objective function of the PFSSP problem is to minimize total energy consumption (TEC) [18, 19]. The following is the PFSSP problem formula:

$$C_{1,1} = S_1 + P_{1,1} + R_{1,1} \tag{1}$$

$$C_{1,j} = \max\left(C_{1,j-1} - R_{1,j-1}, S_1\right) + P_{1,j} + R_{1,j} \ , \qquad j = 2..m \tag{2}$$

$$C_{i,1} = C_{i-1,1} + S_{i-1,i} + P_{i,1} + R_{i,1} \ , \qquad i = 2..n \tag{3}$$

$$C_{i,j} = \max\left(C_{i,j-1} - R_{i,j-1},\ S_{i-1,i} + C_{i-1,j}\right) + P_{i,j} + R_{i,j} \ , i = 2..n, j = 2..m \tag{4}$$

$$B = \sum_{i=1}^{n} P_{i,j} \ , \quad \forall j = 1..m \tag{5}$$

$$S = \sum_{i=2}^{n} S_{i-1,i} + S_1 \ , \quad \forall j = 1..m \tag{6}$$

$$R = \sum_{i=1}^{n} R_{i,j} \quad \forall j = 1..m \tag{7}$$

$$T = \max\left(C_{i,j}\right) \ , \forall i = 1..n,\ j = 1..m \tag{8}$$

$$I = T - B - S - R \ , \ \forall j = 1..m \tag{9}$$

$$T = \sum_{j=1}^{m}(B . P + I . I + S . S + R . R) \tag{10}$$

The PFSSP model was modified from Li, et al. [19]. Best scheduling is defined as having the minimum TEC. The PFSSP model for minimizing energy consumption is as follows

Objective function $Z = \min T$ (11)

Subject to :

$$\left.\begin{array}{l}
C_{1,1} = S_1 + P_{1,1} + R_{1,1} \\
C_{1,j} = \max\left(C_{1,j-1} - R_{1,j-1}, S_1\right) + P_{1,j} + R_{1,j} \ , \qquad j = 2..m \\
C_{i,1} = C_{i-1,1} + S_{i-1,i} + P_{i,1} + R_{i,1} \ , \qquad i = 2..n \\
C_{i,j} = \max\left(C_{i,j-1} - R_{i,j-1},\ S_{i-1,i} + C_{i-1,j}\right) + P_{i,j} + R_{i,j} \ , i = 2..n, j = 2..m \\
B = \sum_{i=1}^{n} P_{i,j} \ , \quad \forall j = 1..m \\
S = \sum_{i=2}^{n} S_{i-1,i} + S_1 \ , \quad \forall j = 1..m \\
R = \sum_{i=1}^{n} R_{i,j} \quad \forall j = 1..m \\
T = \max\left(C_{i,j}\right) \ , \forall i = 1..n,\ j = 1..m \\
I = T - B - S - R \ , \ \forall j = 1..m \\
T = \sum_{j=1}^{m}(B . P + I . I + S . S + R . R)
\end{array}\right\} \tag{12}$$

Equation (1) explains the completion time of work sequence one on machine 1; Equation (2) explains that machines 2 to m; Equation (3) explains the completion time of sequence i work from machine 1; Equation (4) shows that machine j; Equation (5) explains the total machine busy time; Equation (6) explains the total setup time. Equation (7) illustrates the total removal time. Equation (8) shows the completion time of machine j from permutation; Equation (9) shows the total idle time of the permutation machine j; Equation (10) describes the permutation TEC (objective function); Equation (11) explains the objective function of the PFSSP model to minimize energy consumption; and Equation (12) explains the constraints of the PFSSP model to minimize energy consumption. The constraints in this model are equations (1) to (10).

2.2 Proposed Hybrid Whale Optimization Algorithm (HWOA)

WOA was proposed by Mirjalili and Lewis [17] to solve the problem of ongoing optimization. However, it has the characteristics to solve PFSSP. We proposed HWOA, which combines WOA with a local strategy such as flip and swap search. HWOA has three main steps: Initialize the position of the search agent and change the position to permutation with the Large Rank value (LRV) rule, evaluate the WOA, do a local search with flip and swap. These five steps are discussed in the following subsections:

2.2.1 Initialization of search agent positions and convert search agents to job permutations

The initial position of the search agent is generated randomly. It is raised from the upper bound and lower bound range. Initialization of the position of a search agent must ensure that there are no repeating numbers in the same search agent. Furthermore, the number of dimensions in the population matrix of search agent positions is based on the number of jobs. We propose the conversion of search agents to job permutations by applying Large Rank Value (LRV). In LRV, the continuous value of the position of each search agent is sorted from the largest to the smallest.

2.2.2 Whale Optimization Algorithm

Whale Optimization Algorithm (WOA) is a new metaheuristic algorithm developed from the behavior of humpback whales hunting for prey [17]. Following are the steps for the Whale Optimization Algorithm. Humpback whales know the location of prey and then surround their prey. The WOA algorithm assumes that the best solution is a prey target that is close to optimum. After another search, the agent updates the position that approaches the best search agent. Equation (13) and (14) are similarities in behavior around prey.

$$\vec{D} = \left|\vec{C}.\overrightarrow{X^*}(t) - \vec{X}(t)\right| \tag{13}$$

$$\vec{X}(t+1) = \overrightarrow{X^*}(t) - \vec{A}\cdot\vec{D} \tag{14}$$

$\vec{D}$ indicates the position of the distance of the whale to the prey. t denotes iteration. $\vec{A}$ and $\vec{C}$ are vector coefficients. X^* is the vector position of the best solution. $\vec{X}$ is the vector position. $|\ |$ is the absolute value X^* and it must be updated in every iteration if there is a better solution. Vektor $\vec{A}$ and $\vec{C}$ formulated in Equation (15) dan (16).

$$\vec{A} = 2\vec{a}\cdot\vec{r} - \vec{a} \tag{15}$$

$$\vec{C} = 2\cdot\vec{r} \tag{16}$$

$\vec{a}$ decreases linearly from 2 to 0 during the experiment (in the exploration and exploitation phase). $\vec{r}$ is a random vector with a range. Furthermore, the whale attacks using bubbles (the exploitation phase). Mathematical models of behavior to attack humpback whales are designed with the following two approaches: 1). Circle shrinkage mechanism: this behavior is achieved by deriving the value of $\vec{a}$ in equation (15). 2) Updating the spiral position (Equation (17)).

$$\vec{X}(t+1) = \overrightarrow{D'}\cdot e^{bl}\cdot\cos(2\pi l) + \overrightarrow{X^*}(t) \tag{17}$$

$\overrightarrow{D'} = \left|\overrightarrow{X^*}(t) - \vec{X}(t)\right|$ indicates the distance of the whale to prey (the best solution obtained). b is a constant for defining spirals. l is a random number with a range [-1,1]. Mirjalili and Lewis [17] assume that there is a 50% possibility to choose between the mechanism of shrinkage of a circle or a spiral model to renew the position of the whale (Equation (18)). Where p is a random number with a range [0,1]. Furthermore, the Search for prey phase (the exploration phase) is modeled in (Equation (19) and (20)). HWOA pseudo-code is described in algorithm 1.

$$\vec{X}(t+1) = \begin{cases} \overrightarrow{X^*}(t) - \vec{A}\cdot\vec{D} & if\ \ p < 0{,}5 \\ \overrightarrow{D'}\cdot e^{bl}\cdot\cos(2\pi l) + \overrightarrow{X^*}(t) & if\ \ p \geq 0{,}5 \end{cases} \tag{18}$$

$$\vec{D} = \left|\vec{C}\cdot\overrightarrow{X_{rand}} - \vec{X}\right| \tag{19}$$

$$\vec{X}(t+1) = \overrightarrow{X_{rand}} - \vec{A}\cdot\vec{D} \tag{20}$$

2.2.3 The local search

The local search method is a combinatorial optimization method for changing the initial sequence until an optimal objective function is generated. The proposed local search steps are flip and swap. Swap is carried out by swapping two random work sequences. The swap operation iterated to t is repeated as n. Flip is reversing the order in which jobs are selected. The Flip operation in iteration to t is also repeated as n.

2.3 Experimental procedure

The processing time was generated from a uniform random distribution (10.50). The setup time for jobs in the first sequence was generated from the uniform random distribution (1.10). The setup a time for moving from job $i-1$ to job i was generated from a uniform distribution (1,10). The removal time was generated from a uniform random distribution (1,5). The energy consumption needed during processing operations was generated from a uniform random distribution (5,10). Energy consumption was generated from uniform random distribution (1,3). Energy consumption removal was generated from uniform random distribution (1,3). The energy consumption idle machine was generated from uniform random numbers (1,2). To find out the best parameters of the algorithm, we experimented with two parameters. There are two parameters used in this experiment, such as population and iteration. The population consists of 2 levels such as 10, and 100. An iteration consists of 5 levels such as iteration of 10, 50, 100, 200, and 500. Each data was tried ten times. We tried 8 variations of job and machine. Therefore, the experiments carried out 80 experiments. Furthermore, the best parameters of the experimental results compared with some previous algorithms include Genetic Algorithm (GA) [9], particle swarm optimization (PSO) [12], and WOA [17]. Algorithm performance was measured by the Efficiency Index Percentage (EIP). EIP is described as the ratio of energy consumption between the HWOA algorithm and other algorithms as a percentage (equation 21).

$$\text{EIP} = \frac{\overline{T}_{p \quad al}}{\overline{T}_{a \quad al}} x100\% \qquad (21)$$

3. Results and discussion

The results of the HWOA parameter experiment are shown in table 1. It shows that the higher the number of iterations and the number of the population used, the HWOA results in lower energy consumption. For the case of small jobs, the best parameter is to use a small population and iteration. Conversely, for the case of large jobs, the population and iteration used are large. The Efficiency Index Percentage (EIP) assessment of energy consumption in table 2 proves that HWOA provides more significant performance in medium and large cases. Overall, EIP from HWOA energy consumption compared to Genetic Algorithm (GA) [9], particle swarm optimization (PSO) [12], and WOA [17] were 99.61%, 99.70%, and 99.74%. This experiment shows that HWOA performance is better than some other algorithms.

Tabel 1. The experiment of the effect of HWOA parameters on energy consumption

Job	Machine	Population of 10					Population of 100				
		Iteration 10	Iteration 50	Iteration 100	Iteration 200	Iteration 500	Iteration 10	Iteration 50	Iteration 100	Iteration 200	Iteration 500
5	4	4688	4688	4688	4688	4688	4688	4688	4688	4688	4688
5	16	25558	25558	25558	25558	25558	25558	25558	25558	25558	25558
40	4	38593	38656	38577	38647	38714	38699	38638	38579	38606	38488
40	16	157645	157563	157322	157011	156907	157112	156920	156765	156522	156429
60	4	62998	62841	62693	62874	62800	62900	62797	62717	62704	62628
60	16	252238	251453	251383	251353	250995	251019	250959	250828	250697	250316
100	4	92588	92414	92324	92266	92191	92355	92256	92147	92168	92187
100	16	368938	369059	368691	368395	368278	367885	368465	367823	366869	366622

Tabel 2. Comparison of energy consumption and EIP of several other algorithms

Case	EIP			Case	EIP		
	GA	PSO	WOA		GA	PSO	WOA
5 job 4 machine	100,00%	100,00%	100,00%	60 job 4 machine	99,54%	99,78%	99,75%
5 job 16 machine	100,00%	100,00%	100,00%	60 job 16 machine	99,39%	99,56%	99,58%
40 job 4 machine	99,65%	99,67%	99,68%	100 job 4 machine	99,66%	99,80%	99,88%
40 job 16 machine	99,25%	99,36%	99,53%	100 job 16 machine	99,36%	99,39%	99,48%

4. Conclusion

In this article, we propose a hybrid Whale Optimization Algorithm (HWOA) algorithm. Finally, we propose the best parameters for solving the energy consumption case. In the case of small jobs, it is better to use populations and small iterations. Instead, for the case of large jobs, it is better to use population and significant iteration. Furthermore, HWOA is compared to several procedures. Computational experiments prove that HWOA produces optimal energy consumption. Several research areas can be studied for future work. We propose that HWOA can be used as an initial solution for other metaheuristic algorithms. Finally, the offered HWOA algorithm can be applied to reduce energy consumption in the PFSSP problem.

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