A No-Idle Flow Shop Scheduling using Fire Hawk Optimizer to Minimize Energy Consumption

Devisa Restiana Wati [a]*, Ikhlasul Amallynda [a]
[a] Department of Industrial Engineering, Faculty of Engineering, University of Muhammadiyah Malang
Jl. Raya Tlogomas 246 Malang, East Java, Indonesia, 65144
* Corresponding author: devisa.restiana@gmail.com

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ABSTRACT

The current energy crisis is a pressing global challenge, with the industrial sector accounting for half of global energy consumption. Scheduling is considered one of the potential methods to reduce energy consumption. This article introduces the Fire Hawk Optimizer (FHO) algorithm to solve the no-idle flow shop scheduling problem to minimize overall energy consumption. FHO organizes the job sequence in no-idle flow shop scheduling to reduce energy consumption. This research investigates the use of different machine speed levels, namely slow, fast, and normal, based on case data of manufacturing industries in Indonesia. The results of this study compare the performance of the FHO algorithm with the Adaptive Integrated Greedy (AIG) heuristic method and compare it with the Grey Wolf Optimizer (GWO) algorithm. The experimental results showed that total energy consumption tends to be high when processed quickly. Conversely, low speed results in lower energy consumption but requires longer processing time. The comparison results show that the Fire Hawk Optimizer is more efficient in reducing total energy consumption than the AIG heuristic method. Meanwhile, the FHO algorithm performs comparably to the GWO algorithm and completes enumeration. These findings confirm that the proposed procedure can be an alternative to the scheduling optimization process.

1. Introduction

The energy crisis is one of the most pressing environmental challenges that must be addressed now [1, 2]. The impacts of this crisis include the depletion of energy resources and an increase in greenhouse gases due to excessive energy use [3]. The manufacturing sector is the most significant contributor to energy consumption, accounting for half of worldwide energy consumption [4]. Therefore, the manufacturing industry needs to reduce energy use [5]. In the context of the manufacturing industry, energy consumption occurs throughout the production process. However, what requires the most energy is when the machine is idling [3]. Therefore, effective schedule planning is required to reduce energy consumption during production and idle time [6-8]. One of the scheduling methods that

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can be applied to overcome this is the no-idle flow shop scheduling problem, where this method requires machines to work without stopping [9].

Previous studies in optimizing no idle flow shop scheduling problems have proposed various methods to achieve different objectives. Nagano, et al. [10] adopted the greedy algorithm method to minimize flow time. Zhou, et al. [11], In their research, use the Invasive Weed Optimization approach focusing on minimizing completion time or makespan. Shao, et al. [12] Integrating memetic algorithm and edge histogram to reduce completion time. In addition, Shao, et al. [13] propose a local search approach to minimize makespan, and Bektaş, et al. [14] adopted Benders Decomposition to achieve similar results. In his research, Della Croce, et al. [15] utilize the Integer Linear Programming (ILP) formula to minimize makespan. Miri and Allali [16], on the other hand, developed specialized heuristic methods to achieve similar goals.

Meanwhile, Balogh, et al. [17], introduced a MILP (Mixed Integer Linear Programming) based local search procedure to reduce total tardiness in the no-idle flow shop scheduling problem. On the other side, Li, et al. [18] developed the Adaptive Iterated Greedy Algorithm to minimize total flowtime as an effective solution to this problem. Some research also focuses on minimizing energy consumption in the no-idle flow shop scheduling problem. Chen, et al. [19] develop a Collaborative Optimization approach to reduce energy consumption. Al-Imron, et al. [9] used the Grey Wolf Optimizer metaheuristic algorithm to achieve similar results.

Previous research has extensively investigated and developed the no-idle flow shop scheduling problem, focusing mainly on completion time (makespan) minimization as the objective function. However, research focusing on energy consumption in the context of the no-idle flow shop scheduling problem is limited. There is an urgent need to fill this gap to understand further the impact of energy management on operational efficiency in a no-idle time flow shop environment. In addition, innovative algorithms such as Fire Hawk Optimizer (FHO) have never been explored in scheduling optimization, especially for no-idle flow shop scheduling problems. Integrating these algorithms can unlock new potential in improving the performance of solutions to this problem, contributing significantly to the advancement in the no-idle time flow shop scheduling by considering the critical aspect of energy consumption.

In this research, the FHO algorithm was chosen to optimize no idle flowshop scheduling because it has proven effective in various fields. FHO algorithm has been successfully applied to solve various problems such as project scheduling [20], clustering scheme [21], fake News Detection [22], and modeling thermo-hydraulic [23]. Therefore, based on the description, this research aims to develop a new FHO procedure to solve the no-idle flow shop scheduling problem with the objective function of minimizing energy consumption with no-idle flow shop scheduling. This research also proposes a new modified FHO metaheuristic algorithm. FHO is a new algorithm offered by Azizi, et al. [24]. This research also compares the proposed FHO procedure with the heuristic method Adaptive Iterated Greedy Algorithm. (AIGA) [18] and Grey Wolf Optimizer metaheuristic algorithm (GWO) [25]. This research is expected to be an alternative to solving the energy crisis experienced by the manufacturing industry.

The main contribution of this research lies in the innovative FHO procedure applied to optimize the scheduling problem in the context of no idle flow shop scheduling. By focusing on the objective function of minimizing energy consumption, this research contributes significantly to operational efficiency. It potentially reduces the environmental impact of manufacturing activities. The results of this study are also expected to provide practical guidance for industries and decision-makers to implement FHO procedures to improve production efficiency while minimizing energy consumption, which can reduce

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environmental impact. In addition, the findings from this study can also serve as a foundation for further research in developing more advanced and sustainable scheduling methods to solve the no-idle flow shop scheduling problem.

2. Methods

2.1 Assumptions, Notations, and Mathematical Models

This section describes the assumptions, notations, and mathematical models used in the study. The assumptions used include (1) all jobs must be processed using the same process sequence on the machine. (2) All jobs arrive and are ready to be processed at time 0. (3) In order to fulfill the requirement of no-idle, the start time of processing the first job on the second machine until the m-th machine must be delayed. (4) Each machine can only process one job at a time, and one job can only be processed once on each machine. (5) When the first job starts processing, it cannot be stopped until the last job is completed. (6) Setup time is included in the job processing time. (7) No machine can be idle to wait for the next job to be processed.

In addition, the notation used is as follows:

n = Number of jobs
m = Number of machines
i = Job Index
j = Machine index
r = Machine speed index level
$C_{i,j}$ = Completion time of job i and machine j
S_j = Start time at machine j
F_j = Completion time on machine j
$P_{i,j}$ = Processing time of job i on machine j
C_{max} = Makespan or completion time
μ_r = Machine speed
τ_j = Processing energy consumption on machine j
λ_r = Processing energy transformation coefficient for level $l \in L$
φ_j = Energy consumption when machine j is idling
TEC = Total energy consumption
Y_{ijr} = 1, if job i is processed with speed rate r on machine j ; otherwise 0
X_{ik} = 1, if job k is preceded by job i; 0, otherwise (i<k)
C_{ij} = completion time of i-th job on j-th machine
θ_j = j-th machine idle time
S_j = start time of the j-th machine

Furthermore, the mathematical model used in NIPFSP to minimize energy consumption is as follows:
Objective function:

$$\text{Min TEC} \tag{1}$$

Constraints:

$$c_{i,1} \geq \sum_{r=1}^{l} \frac{P_{i1}Y_{ijr}}{\mu_r} \ \forall_i = (1, \dots, n) \tag{2}$$

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$$c_{i,j} - c_{i,j} - 1 \geq \sum_{r=1}^{l} \frac{P_{i1}Y_{ijr}}{\mu_r} \qquad \forall_i = (2, \dots, m), i = (2, \dots, n) \tag{3}$$

$$c_{ij} - c_{kj} + DX_{ik} \geq \sum_{r=1}^{l} \frac{P_{i1}Y_{ijr}}{\mu_r} \quad \forall_i = (1, \dots, n), j = (1, \dots, m), k = (1, \dots n) \tag{4}$$

$$c_{ij} - c_{kj} + DX_{ik} \geq D - \sum_{r=1}^{l} \frac{P_{i1}Y_{ijr}}{\mu_r} \qquad \forall_i = (1, \dots, n), j = (1, \dots, m), k = (1, \dots n) \tag{5}$$

$$c_{max} \geq c_{min} \; \forall_i = (1, \dots, n) \tag{6}$$

$$\sum_{r=1}^{l} Y_{ijr} = 1 \; \forall_i = (1, \dots, n), j = (1, \dots, m) \tag{7}$$

$$Y_{ijr} = Y_{i,j+1,r} \; \forall_i = (1, \dots, n), j = (1, \dots, m), r = (1, \dots, l) \tag{8}$$

$$\theta_j = c_{max} - \sum_{i=1}^{n} \sum_{r=1}^{l} \frac{P_{i1}Y_{ijr}}{\mu_r} \; \forall_j = (1, \dots, m) \tag{9}$$

$$S_j \leq c_{ij} - \sum_{r=1}^{l} \frac{P_{i1}Y_{ijr}}{\mu_r} \; \forall_i = (1, \dots, n), j = (1, \dots, m) \tag{10}$$

$$S_j \leq c_{ij} \; \forall_i = (1, \dots, n), j = (1, \dots, m) \tag{11}$$

$$S_j \leq c_{ij} + \sum_{i=1}^{n} \sum_{r=1}^{l} \frac{P_{i1}Y_{ijr}}{\mu_r} \; \forall_i = (1, \dots, n), j = (1, \dots, m) \tag{12}$$

$$\text{TEC} = \sum_{i=1}^{n} \sum_{j=1}^{m} \sum_{r=1}^{l} \frac{P_{ij}\tau_j\lambda_r}{60\mu_r} Y_{ijr} + \sum_{j=1}^{m} \frac{\varphi_j\theta_j\tau_j}{60} \tag{13}$$

$$S_j = S_{j-1} + Max_{1 \leq h \leq n}\left\{\sum_{j=1}^{h} P_{(i),j-1} - \sum_{j=1}^{h-1} P_{(i),j}\right\}, \text{ j = (2,3,…,m)} \tag{14}$$

The objective function of this research is TEC minimization in Equation (1). Constraint (2) is the time required to complete each job. Equation (3) ensures that the next operation will be processed if the previous operation has been completed. Equations (4) and (5) are the order of each job. Equation 6 is the calculation of the makespan. Equations (7) and (8) are to ensure that each job is processed on all machines at the same machining speed. Equation (9) shows the idle time on each machine. Equations (10), (11), and (12) are used to ensure that no idling occurs between jobs on each machine. Equation (13) is the calculation formula of TEC minimization. Researchers must understand when machines can operate without idling between jobs in this no-idle flow shop. The formula for solving the machining start time can be seen in Equation (14).

2.2 Fire Hawk Optimizer Algorithm

This section presents a proposed algorithm for optimizing the no-idle flow shop scheduling problem. FHO is a new metaheuristic algorithm inspired by the foraging behavior of the soul, pariah, and brown eagle. When this bird catches its prey in nature by burning, it is called the Fire Hawk. There are steps in the discussion of this algorithm, namely (1) the initialization stage to determine the initial position. (2) Evaluate the objective function by considering the optimization problem. This aims to determine the location of the fire hawk. (3) Fire Hawk collects sticks to burn the selected area. (4) Update the position of the prey movement in the fire hawk area. In the solution, in each iteration, the best solution is obtained. The pseudocode of the Fire Hawk Optimizer in Algorithm 1 is presented.

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The initialization is used to identify the initial position of the vector in the search space. The population of the Fire Hawk is modeled in Equation (15). The position of the Fire Hawk is randomly generated using minimum and maximum constraints. This position is modeled in Equation (16).

$$PR = \begin{bmatrix} X_1 \\ X_2 \\ \cdot \\ \cdot \\ \cdot \\ X_k \\ \cdot \\ \cdot \\ \cdot \\ X_m \end{bmatrix} = \begin{bmatrix} X_1^1 X_1^2 \dots X_1^j \dots X_1^d \\ X_2^1 X_2^2 \dots X_2^j \dots X_2^d \\ \cdot \quad \cdot \quad \cdot \quad \cdot \\ \cdot \quad \cdot \quad \cdot \quad \cdot \\ \cdot \quad \cdot \quad \cdot \quad \cdot \\ X_i^1 X_i^2 \dots X_i^j \dots X_i^d \\ \cdot \quad \cdot \quad \cdot \quad \cdot \\ \cdot \quad \cdot \quad \cdot \quad \cdot \\ \cdot \quad \cdot \quad \cdot \quad \cdot \\ X_N^1 X_N^2 \dots X_N^j \dots X_N^d \end{bmatrix}, \{ {i=1,2,\dots,N. \atop j=1,2,\dots,d.} \tag{15}$$

$$X_i^j(0) = X_{i,min}^j + rand.\left(X_{i,max}^j - X_{i,min}^j\right), \{ {i=1,2,\dots,N. \atop j=1,2,\dots,d.} \tag{16}$$

Then, the fire hawk will look for a fire stick to burn the selected area to confine the prey. The latest fire hawk position is shown in Equation (17).

$$FH_l^{new} = FH_l + (r_1 \times GB - r_2 \times FH_{near}) \tag{17}$$

Next, determine a safe place for the fire hawk where this place is a safe place for its prey to survive the danger. This position is modeled by Equation (18).

$$SP_l = \frac{\sum_{q=1}^{t} PR_q}{r}, \{ {q=1,2,\dots,r \atop l=1,2,\dots,n} \tag{18}$$

After the prey moves to avoid the dangerous area, the position of the prey will change. This prey position update is shown in Equation (19).

$$PR_q^{new} = PR_q + (r_3 \times FH_l - r_4 \times SP_l), \{ {l=1,2,\dots,n \atop q=1,2,\dots,r} \tag{19}$$

Finally, calculate the position of a safe place outside the lth fire hawk with Equation (20) and determine the position of prey can be closer to the fire hawk near the ambush or even try to hide in a safer place outside the fire hawk area with Equation (21). This research proposes the Large Rank Value (LRV) procedure to convert the positions of fire hawks to job sequences in the no-idle flow shop scheduling problem. LRV is an easy-to-apply procedure to convert job sequences to job sequences [26-28].

$$SP = \frac{\sum_{k=1}^{m} PR_k}{m}, k = 1,2,\dots,m \tag{20}$$

$$PR_q^{new} = PR_q + (r_5 \times FH_{alter} - r_6 \times SP), \{ {l=1,2,\dots,n \atop q=1,2,\dots,r} \tag{21}$$

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Algorithm 1: Pseudocode of Fire Hawk Optimizer

```
Procedure Fire Hawk Optimizer (FHO)
        Determine initial positions of solution candidates (Xi) in the search space with
        N candidates.
        Apply LRV to convert the FHO position to job sequence
        Evaluate fitness values for initial solution candidates
        Determine the Global Best (GB) solution as the main fire
        While Iteration < Maximum number of iterations
            Generate n as a random integer number for determining the number of
            Fire Hawk
            Determine Fire Hawks (FH) and Preys (PR) in the search space
            Calculate the total distance between the Fire Hawks and the prey
            Determine the territory of the Fire Hawks by dispersing the prey
            for l=1:n
                Determine the new position of the Fire Hawks by Eq.17
                for q=l:r
                    Calculate the safe place under lth Fire Hawk territory by Eq.18
                    Determine the new position of the prey by Eq.19
                    Conversion of the position fire hawk to sequence permutation
                    using LRV
                    Calculate the safe place outside lth Fire Hawk territory by Eq.20
                    Determine the new position of the prey by Eq.21
                end
            end
            Apply LRV to convert the FHO position to a job sequence
            Evaluate fitness values for initial solution candidates
            Determine the Global Best (GB) solution as the main fire
        end while
        Return GB
end Procedure
```

2.3 Data Collection

In this study, research data was obtained through a case study at a manufacturing company in Indonesia through three machines. The first case involves ten jobs executed on a no-idle flow shop system, with details of the processing time listed in Table 1. The second case also involved ten jobs, with further information in Table 2. Furthermore, the fourth case involved twelve jobs, described in detail in Table 3. Table 4 provides a more detailed overview of the processing time in the fourth case, which involves ten jobs.

Meanwhile, the machine speed coefficients and parameters can be found in Table 5. In addition, information regarding the electrical energy consumption of the machine under idle conditions and at slow, normal, and fast speeds is presented in Table 6. The data obtained from these various cases provides a robust empirical basis for analysis and formulation of recommendations to improve operational efficiency within the scope of no idle flow shop scheduling.

Table 1. Processing Time for Case 1 (Minutes)

Job	Machines		
	M1	M2	M3
J1	211.077	578	192.581
J2	1055.385	2890	962.907
J3	316.615	867	288.872
J4	105.538	289	96.291
J5	158.308	433.5	144.436
J6	8.443	23.12	7.703
J7	10.554	28.9	9.629
J8	8.443	23.12	7.703
J9	158.308	433.5	144.436
J10	211.077	578	192.581

Table 2. Processing Time for Case 2 (Minutes)

Job	Machines		
	M1	M2	M3
J1	263.846	722.5	240.727
J2	105.538	289	96.291
J3	10.554	28.9	9.629
J4	158.308	433.5	144.436
J5	105.538	289	96.291
J6	1055.385	2890	962.907
J7	105.538	289	96.291
J8	105.538	289	96.291
J9	158.308	433.5	144.436
J10	211.077	578	192.581

Table 3. Processing Time for Case 3 (Minutes)

Job	Machines		
	M1	M2	M3
J1	211.08	578	192.58
J2	211.08	578	192.58
J3	263.85	722.50	240.73
J4	211.08	578	192.58
J5	1055.38	2890	962.91
J6	263.85	722.50	240.73
J7	10.55	28.90	9.63
J8	10.55	28.90	9.63
J9	8.44	23.12	7.70
J10	8.97	24.57	8.18
J11	9.50	26.01	8.67
J12	8.44	23.12	7.70

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Table 4. Processing Time for Case 4 (Minutes)

Job	Machines		
	M1	M2	M3
J1	15.83	43.35	14.44
J2	10.55	28.90	9.63
J3	15.83	43.35	14.44
J4	1583.08	4335.00	1444.36
J5	1055.38	2890.00	962.91
J6	10.55	28.90	9.63
J7	10.55	28.90	9.63
J8	21.11	57.80	19.26
J9	36.94	101.15	33.70
J10	31.66	86.70	28.89

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Table 5. Speed Parameter

Coefficients	Machines	Speed Levels		
		Slow	Normal	Fast
μ_r	1	1.096	1	0.929
	2	1.064	1	0.588
	3	1.089	1	0.945
λ_r	1	1.780	1	0.730
	2	1.169	1	0.892
	3	1.356	1	0.774
φ_j	1	1.224	0.688	0.502
	2	0.196	0.168	0.150
	3	0.672	0.496	0.384

Table 6. Engine electrical energy consumption at idle and at slow, normal, fast speeds

Machines	Energy Consumption (τ_j)(Kwh)			
	Idle	Slow	Normal	Fast
M1	0.585	1.171	2.085	2.858
M2	5.585	29.874	34.912	39.141
M3	2.401	3.573	4.844	6.261

2.4 Experiment procedure

In this study, we conducted a series of experiments focusing on no idle flow shop scheduling. The key parameters used in the experiments include iteration and population, which are 200, 400, 600, and 250, 500, 750, respectively, with the experiment process conducted through Matlab R2018a software. Each case was run based on these parameter settings. The results of each experiment were carefully recorded, covering vital scheduling parameters such as makespan, process energy, idle energy, and total energy consumption. Furthermore, this study attempts to compare the performance of the proposed FHO procedure with the Adaptive Iterated Greedy Algorithm (AIGA) heuristic method [18], metaheuristic algorithm Grey Wolf Optimizer (GWO) [25], and a complete enumeration

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procedure. The study also presents six energy consumption reduction strategies that involve adjusting the speed level of each machine. It provides a comprehensive overview of the impact of the proposed procedure on efficiency improvement in energy consumption reduction.

3. Results and Discussion

3.1 Result of FHO Algorithm

The optimization results of the proposed FHO method in cases 1 to 4 are presented in Table 7 - Table 10. The results show that with small iterations and populations (200 and 250), the proposed algorithm provides a solution that is as good as if run with significant iterations and populations. This result indicates that the FHO procedure can find the optimal solution to the no idle flow shop scheduling problem with small iterations and population which allows it to be solved quickly.

The FHO procedure can find optimal solutions with relatively small iterations and populations, allowing fast solutions. It happens because FHO utilizes natural algorithms inspired by the behavior of groups of birds of prey [23]. Birds of prey tend to work collaboratively and efficiently in searching for prey, so FHOs can mimic this strategy to achieve convergence of optimal solutions quickly [22]. Moreover, the adaptation mechanism in FHO allows the algorithm to dynamically adjust its strategy during the search process, focusing resources on promising regions [21]. Thus, FHO can efficiently optimize the solution space search even with a limited population and iterations. It enables FHO to be a very effective tool in handling scheduling problems, especially in cases where time and computational resource constraints become critical factors [20].

3.2 Comparison of procedures

The comparison of procedures to minimize total energy consumption in no idle flow shop scheduling is presented in Table 11. The results show that the proposed algorithm can produce a much more optimal solution than the AIGA procedure. In addition, the proposed procedure also provides a solution comparable to the complete enumeration procedure and the GWO algorithm in terms of the quality of the resulting solution. It is evident from all alternative solutions presented in the complete enumeration procedure the proposed procedure produces the same solution. This result shows that the proposed procedure can be an alternative for optimizing no-idle flow shop scheduling.

Table 7. Optimization results of the proposed FHO method in Case 1

Iterations	Populations	EI	EP	TEC
200	250	177.739	6336.578	6514.318
	500	177.739	6336.578	6514.318
	750	177.739	6336.578	6514.318
400	250	177.739	6336.578	6514.318
	500	177.739	6336.578	6514.318
	750	177.739	6336.578	6514.318
600	250	177.739	6336.578	6514.318
	500	177.739	6336.578	6514.318
	750	177.739	6336.578	6514.318

The proposed FHO procedure can generate good solutions by incorporating several important aspects in the solution search process. FHO adopts a search mechanism inspired by the behavior of groups of birds of prey that work collaboratively to find prey [29]. It allows the FHO to explore the solution space efficiently. FHO also has an adaptation mechanism that allows the algorithm to explore promising regions in the search space [30]. In addition, FHO can maintain a balance between exploration and exploitation, which enables the search for an optimal solution without getting stuck in a local minimum [21].

Table 8. Optimization results of the proposed FHO method in Case 2

Iterations	Populations	EI	EP	TEC
200	250	182.475	6437.916	6620.39
	500	182.475	6437.916	6620.39
	750	182.475	6437.916	6620.39
400	250	182.475	6437.916	6620.39
	500	182.475	6437.916	6620.39
	750	182.475	6437.916	6620.39
600	250	182.475	6437.916	6620.39
	500	182.475	6437.916	6620.39
	750	182.475	6437.916	6620.39

Table 9. Optimization results of the proposed FHO method in Case 3

Iterations	Populations	EI	EP	TEC
200	250	189.370	6418.543	6607.914
	500	189.370	6418.543	6607.914
	750	189.370	6418.543	6607.914
400	250	189.370	6418.543	6607.914
	500	189.370	6418.543	6607.914
	750	189.370	6418.543	6607.914
600	250	189.370	6418.543	6607.914
	500	189.370	6418.543	6607.914
	750	189.370	6418.543	6607.914

Table 10. Optimization results of the proposed FHO method in Case 4

Iterations	Populations	EI	EP	TEC
200	250	423.878	7883.467	8307.345
	500	423.878	7883.467	8307.345
	750	423.878	7883.467	8307.345
400	250	423.878	7883.467	8307.345
	500	423.878	7883.467	8307.345
	750	423.878	7883.467	8307.345
600	250	423.878	7883.467	8307.345
	500	423.878	7883.467	8307.345
	750	423.878	7883.467	8307.345

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Table 11. Comparison of procedures based on total energy consumption

Case	AIGA	FHO	GWO	Enumeration complete
1	6653.57	6514.318	6514.318	6514.318
2	6665.28	6620.39	6620.39	6620.39
3	6621.39	6607.914	6607.914	6607.914
4	8330.15	8307.345	8307.345	8307.345

3.3 Energy efficiency strategy

This research explores alternative solution scenarios by varying the speed of the machines used, in contrast to the previous practice where the company used fast speeds for all machines. This change in machine speed has produced alternative solutions that can be applied to the scheduling case at hand. Table 12 shows a selection of machine speed scenarios that have been identified. The analysis results show that in scenario 1, scenario 5, using normal speed for machines 1-3 provides the lowest total energy consumption, 3395.69 kWh. Complete information about the results of all alternative scenarios in case 1 is presented in Table 13.

Table 12. Machine speed strategy scenarios

Scenarios	Machines		
	M1	M2	M3
1	Normal	Fast	Slow
2	Slow	Fast	Fast
3	Fast	Fast	Normal
4	Slow	Fast	Normal
5	Normal	Normal	Normal
6	slow	slow	slow

Table 13. Optimization results for each scenario in case 1

Scenarios	Makespan	EI	EP	TEC
1	8460.68	235.70	6515.11	6750.80
2	8525.30	486.93	6412.04	6898.97
3	6453.05	163.35	6373.19	6536.54
4	9074.10	426.38	6446.87	6873.25
5	6751.50	228.78	3166.91	3395.69
6	10490.60	348.82	3104.33	3453.15

Table 14-Table 16 describes optimization results for each scenario in Case 2-4. The results showed that in case 2, scenario 5 using normal speed for all machines resulted in the lowest total energy consumption of 3444.17 kW. The same was observed in case 3, where scenario 5, using normal speed, resulted in the smallest total energy consumption of 3434.90 kWh. In case 4, it was noted that the use of normal speed for all three engines resulted in the lowest energy consumption of 1388.62 kWh in scenario 4. The analysis of all four cases shows that engine speed is vital in determining energy consumption. The results showed that using fast speeds on all three machines resulted in higher energy consumption but less significant reduction in makespan. More importantly, the finding of this study is that scenario 5, with the use of normal speed for all three machines, produced

the lowest total energy consumption and relatively small makespan among all the scenarios tested. It indicates that using normal machine speeds is a more efficient in managing energy consumption.

In the no idle flow shop scheduling problem to minimize energy consumption, the use of different machine speeds can significantly impact the total energy consumed. It is because fast machine speed settings require more energy to operate, while normal speed settings are more energy efficient [31]. This study also found that using speed levels can help minimize energy consumption in flow shop problems. Therefore, it is essential to carefully consider the impact of machine speed settings on energy consumption in scheduling problems to minimize energy consumption [32].

Table 14. Optimization results for each scenario in Case 2

Scenarios	Makespan	EI	EP	TEC
1	8406.60	199.44	6619.30	6818.74
2	8402.45	437.35	6514.59	6951.94
3	6547.59	165.12	6475.12	6640.23
4	9153.48	426.06	6549.97	6976.02
5	6803.20	226.62	3217.55	3444.17
6	10383.77	409.48	3154.99	3564.46

Table 15. Optimization results for each scenario in Case 3

Scenarios	Makespan	EI	EP	TEC
1	8555.33	246.93	6599.38	6846.31
2	8332.91	437.34	6494.98	6932.32
3	6805.04	178.25	6455.63	6633.88
4	9138.30	426.12	6530.26	6956.38
5	6793.32	227.03	3207.87	3434.90
6	10410.56	395.46	3145.50	3540.96

Table 16. Optimization results for each scenario in Case 4

Scenarios	Makespan	EI	EP	TEC
1	11964.55	467.27	8105.58	8572.85
2	11955.29	655.99	7977.36	8633.34
3	10212.74	415.41	7929.02	8344.43
4	12316.51	700.99	8020.68	8721.67
5	9575.70	474.92	3940.01	4414.94
6	14465.66	576.18	1374.41	4439.58

3.4 Implication

The findings of this study have significant theoretical implications in the context of no-idle flow shop scheduling. Introducing the Fire Hawk Optimizer (FHO) algorithm as a solution method shows great potential in achieving optimal solutions to this problem, even with limited iteration and population settings, enabling efficient solutions quickly. It shows that heuristic approaches such as FHO can be a promising alternative to tackle energy-constrained scheduling problems. Moreover, the comparison results between FHO and the AIG heuristic method provide strong evidence that FHO has higher efficiency in reducing total energy consumption. These findings open up the potential to apply FHO in real industrial scenarios where energy efficiency is crucial. Moreover, the comparable performance between FHO, Grey Wolf Optimizer (GWO), and complete enumeration

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shows that FHO is a competitive and viable option for various no-idle flow shop scheduling contexts. Thus, these findings make a practical contribution to improving operational efficiency in production and enrich the theoretical insights in developing more effective and efficient scheduling methods.

The practical implications of the findings of this study are significant in the context of no idle flow shop scheduling. The use of high speeds on all three machines, while increasing energy consumption, does not provide a significant improvement in reducing makespan. In contrast, prioritizing using normal speeds for all three machines can result in a more efficient optimal balance between energy consumption and makespan. It shows that the machine speed management strategy is crucial for production efficiency in a no-idle flow shop scheduling situation. Therefore, normal machine speeds can be recommended as a wiser choice to manage energy consumption and improve operational efficiency. These findings can provide valuable guidance for practitioners and production managers in optimizing the performance of their production systems in similar situations.

4. Conclusion

In this study, the Fire Hawk Optimizer (FHO) algorithm is introduced as a solution to the no-idle flow shop scheduling problem to minimize the overall energy consumption. The comparison results show that FHO is significantly more efficient in reducing total energy consumption than the AIG heuristic method. In addition, the performance of FHO is comparable to that of GWO and complete enumeration algorithms. The study also revealed that high speed on the three machines could increase energy consumption but have a less significant effect on reducing makespan in the no-idle flow shop scheduling problem. More importantly, the findings confirmed that using normal speed for all three machines resulted in the lowest total energy consumption and relatively small makespan among all the scenarios tested. It indicates that maintaining normal machine speeds is the best option to manage energy consumption in the no-idle flow shop scheduling problem.

The limitation of this research lies in the limited focus on the no-idle flow shop scheduling problem considering specific machine speed configurations. For future research, it is recommended to expand the scope by exploring a variety of more complex scheduling problems and integrating the context of real-world situations. It is also important to consider additional factors affecting energy consumption, such as different machine types or diverse energy sources. Furthermore, comparing the performance of the Fire Hawk Optimizer (FHO) with other algorithms that have not been explored in this research can provide deeper insights. Finally, a suggestion for future research is to explore solving multi-objective problems to simultaneously minimize energy consumption and makespan. By considering these steps, future research can bring a more comprehensive understanding and optimized solutions for scheduling and managing energy consumption.

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