African Buffalo Optimization for Solving Flow Shop Scheduling Problem to Minimize Makespan

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Abstract. In this paper, African Buffalo Optimization is proposed to solve the flow-shop Scheduling Problem (FSP). The FSP involves n-job that was processed in m-machine. The aim is to reduce the makespan of the whole process. In this study, we also compare the African Buffalo Optimization with an exact solution and other meta-heuristic methods, such as Particle Swarm Optimization (PSO), Hybrid Genetics Algorithm, and also Crow-search Algorithm (CSA) to know the performance of the methods in solution quality and computational time. Friedman test showing African Buffalo Optimization gives an optimal solution in solution quality, the same result with the exact solution, PSO, and hybrid GA.

1. Introduction
In the manufacturing and service industries, scheduling becomes an important role in the decision-making process. Also, scheduling and effective sequencing become necessary in surviving in those industries [1]. In the scope of deterministic machine scheduling, optimization, approximation algorithms, and complexity results are used to overcome problems that involving parallel or single machine, job shop, open shops, and flow shops [2].

Flow shop is a type of scheduling in which the duty sequence of each job is set and every job comes to the work machines or stations for the same processing order [3]. In the Flow-shop scheduling problem (FSP) m different machines {M_1,..., M_m} must process n independent jobs {J_1,...,J_n}. Each job is consists of m operations where each operation needs a distinct machine. The operation on the machine i of job j is denoted O_{ij}. Each operation also needs processing time p_{ij}[4].

Meta-heuristic and heuristic is also kind of exact methods that are used to solve FSP. The exact method gives the optimal problem solution. Yet, the exact method becomes impractical for large flow shop problems because of the complexity raises. Large size FSPs are included in the NP-hard problem class. Hence, heuristic and meta-heuristics methods are used to overcome this kind of problem [5]. Meta-heuristics methods are a set of strategies to increase the heuristic procedures efficiency [6]. Meta-heuristics could give a better result that comes from heuristics at first. It also has an objective to give efficient and detailed optimized output for an optimized schedule of jobs, which decreases the computational time [7].

Many meta-heuristics methods have been used by researchers to solve FSP, such as Iterated Greedy Algorithms [8]–[10], and Hybrid Genetic Algorithm [11], [12]. Other methods for solving FSP are Hybrid Ant Colony algorithm (ACO) [13], Cuckoo Search algorithm [14], Particle Swarm Optimization (PSO) [15]–[17] and Crow search algorithm (CSA) [18]. But, our research proposed to...
Improve African Buffalo Optimization (IABO) for solving the flow shop scheduling problem. African Buffalo Optimization (ABO) was introduced by [19], this algorithm shows better performance on the Traveling Salesman Problem [20], Asymmetric TSP [21] and the design of PID Controller in Automatic voltage regulator system [22], when compared with SA, GA, PSO, ACO, and Randomized Insertion Algorithms. BFO has also been used by [23] in choosing a biodiversity conservation scope with a budget that is limited and [24] in the Low carbon Flexible job shop scheduling problem.

In our research, we use the basic ABO method that has been promoted by [25]. We compared IABO with an exact solution and other meta-heuristics methods, such as PSO, CSA, and Hybrid Genetic Algorithm, to find out the performance of the proposed method in solving the Flow shop scheduling problem. The choice of that methods is because PSO, CSA, Hybrid Cross entropy, and Genetic Algorithm have better performance better results in terms of time calculation and optimum solution compare with other algorithms for solving scheduling problems [12], [17], [18].

2. Research Methodology

2.1. Data collecting.
Data is the real problem of a muffler industry in Purbalingga. Muffler industry which is the object produces several types of car muffler products and motorcycle muffler (n-products) that are processed on the m-machine. The process of production of mufflers was done semi-manually, with some processes using the machine of production [25]. The process of production includes rolling plates with beatings, cutting plates, cutting with cutting grinders, welding, assembly, and finishing. The data needed is the processing time of each job on each machine and the number of jobs. Data is collected in 24 days for the type and number of jobs. Retrieval of data at the beginning of the processing time is repeated 10 times to get the standard time in each process. In calculating the standard time, the adequacy test and uniformity test are carried out first. Retrieval of processing time data is taken if the data are not sufficient. The standard time calculated will be the job processing time on each machine used in the experiment.

2.2. Data Processing

2.2.1 Flow Shop Scheduling Model. This is a flow shop scheduling model to minimize makespan.
Objective function:

\[
\text{Min} \left( \sum_{i=1}^{n} \sum_{j=1}^{m} \sum_{p=1}^{k} Y_{(j,p)} \times W_{(i,p)} \right)
\]  

Subject to:

\[
\sum_{p=1}^{k} Y_{(j,p)} = 1, \quad j \forall 1, 2, ..., m
\]  

\[
\sum_{j=1}^{m} Y_{(j,p)} = 1, \quad p \forall 1, 2, ..., k
\]  

\[
C_{(1,1)} = \sum_{j=1}^{n} W_{(1,j)} \times Y_{(j,1)}
\]  

\[
C_{(1,p)} \geq C_{(1,p-1)} + \sum_{j=1}^{n} W_{(1,j)} \times Y_{(j,p)}
\]  

\[
C_{(i,1)} \geq C_{(i-1,1)} + \sum_{j=1}^{n} W_{(i,j)} \times Y_{(j,p)}
\]  

\[
C_{(i,p)} \geq C_{(i,p-1)} + \sum_{j=1}^{n} W_{(i,j)} \times Y_{(j,p)}
\]  

\[
Y_{(j,p)} \forall (0,1)
\]  

Our model has a binary solution with Eq. 1 is our objective function to minimize makespan. The value of \( Y_{(j,p)} \) is the decision variable of the model, where the value of \( Y_{(j,p)} \) is 1 if job j is assigned to position p. Whereas \( W_{(i,j)} \) is the time processing of job j on machine i. Equation (2) until (9) are constraints of the model. Equation (2) ensures that only 1 job is processed at each position p and
equation (3) ensures that each position gets a job. Equation (4) ensures job in position p cannot start until a job in position p-1 finishes. Equation (5) ensures jobs on machine 1 have no predecessors. Equation (6) ensures a job in position on the machine i cannot start until it finishes on i-1. Equation (7) ensures job in position p cannot start on m until the previous job finishes on i. Equation (8) ensures a job in position on the machine i cannot start until it finishes on i-1. And equation (9) shows Y_{ij,p} has a value of 0 or 1.

2.2.2 Proposed Algorithm. African Buffalo Optimization (ABO) is included in swarm intelligence optimization. This algorithm emulated migration from African Buffalo in search of lush grazing land. [26] These are the two basic sounds of the African Buffalos with which they are able to organize themselves to search for food and defend themselves whenever they are attacked. The "maaa" sound tells the buffalos to stay on to exploit their environment since it is safe and has sufficient pastures and "waaa" sounds used to mobilize the buffalos to move on to explore the search space. Each African buffalo will choose the best position in relation to the target solution and compare it with the previous position that has been stored in memory. The animals move to explore other locations depending on the democratic equation (eq.11) [25]. The ABO algorithm for flow shop scheduling problems in this study is as follows:

1. Initialization: randomly place buffalos to nodes at the solution space by generating a random number (r0) of m x k for the solution of matrix Y a number of N (Y=[Y1, Y2, ..., YN]). For the FSP problem in our research, solution taken binary value, where 1 denotes job i processed in position k, 0 otherwise. How to transform fraction into zero-one value can be done by:

\[ Y_{ik} = \begin{cases} 1, & \text{if } r0 \leq p0 \\ 0, & \text{otherwise} \end{cases} \]  

(9)

Where p0 is the probability of success in the initial matrix [27].

2. Update the buffalo’s fitness value using equation (10)

\[ w_{t+1} = w_t + l_p r_1 (b g_{max} - m_t) + l_p r_2 (b g_{max} - m_t) \]  

(10)

where m_t and w_t describe exploitation and exploration during iteration t. Moves respectively from b^0 buffalo (b = 1, 2, ..., N), depending on l_p and r_1 and r_2 are random numbers between [0,1]. b_{g_{max}} is the best fitness and b_{p_{max}} is the best position for individual buffalos.

3. Update the location buffalo b (bp_{max, b} dan bg_{max,b}) using equation (11)

\[ m_{t+1} = \lambda (w_t + m_t) \]  

(11)

4. Judge whether bg_{max} is updating. If yes, go to step 5, otherwise, go to step 1

5. If the termination condition is met. If yes, go to step 6, otherwise, go to step 2

6. End the procedure. Output best solution

2.2.3 Experiment. The optimization model was solved using the proposed algorithm (ABO). Here, we applied the model to the real case of muffler production. To assess the performance of the proposed algorithm, we divided data into 3 types, which is 8 days 16 days and 24 days. Experiment with other meta-heuristics methods using parameters as shown in Table 1. To achieve an optimal solution, ABO uses the parameters l_p, 0.4 and l_p, 0.2, PSO uses the parameters of the value range inertia p_{max} = 0.9 and \rho_{in} = 0.4, CSA uses the parameters of awareness probability AP = 0.1 and flight length fl = 0.2. The third metaheuristics method using 2 parameters setting, but hybrid GA uses 3 parameters that are smoothing coefficient \alpha = 0.9, mutation parameter c_{m} = 0.1 and cross over parameter c_{c} = 0.8. Experiment with African Based Optimization algorithm and other meta-heuristic methods using population size 100 and the number of iteration 40. To ensure proposed algorithm performance and to prove its ability in FSP, this section compares the solution of the proposed method (ABO) with several well-known meta-heuristics methods: Hybrid GA, PSO, and CSA. We also give a statistical test for experimental results and computational time. In this research, the proposed method (ABO) also will be
compared with the exact solution from LINGO. The comparison is done with the Friedman test statistical test.

3. Result and Discussion
In 24 days, a muffler production in Purbalingga has 47 jobs that processed in 6 machine departments, cutting plates, rolling plates with beatings, cutting with cutting grinders, assembly, welding, and finishing. This is the number of data set:

Table 1. The number of data set

| No. | Data Type       | Number of Job |
|-----|-----------------|---------------|
| 1   | Type 1 (8 days) | 17            |
| 2   | Type 2 (16 days)| 39            |
| 3   | Type 3 (24 days)| 47            |

Experiments were carried out for the exact method with LINGO, ABO, Hybrid GA, PSO, and CSA. Table 2 shown the experiment results in the best minimum makespan of 30 times models testing, and the average computational time is shown in Table 3.

Table 2. Minimize makespan (in a second)

| Data type | Exact solution | ABO | Hybrid GA | PSO | CSA |
|-----------|----------------|-----|-----------|-----|-----|
| Type 1    | 200530.5       | 200530.5 | 200530.5 | 200530.5 | 201498.5 |
| Type 2    | 447510.4       | 447510.4 | 447510.4 | 447510.4 | 447510.4 |
| Type 3    | 530493.7       | 530493.7 | 530493.7 | 530493.7 | 530493.7 |

Table 3. Computational time (in a second)

| Data type | ABO  | Hybrid GA | PSO  | CSA  |
|-----------|------|-----------|------|------|
| Type 1    | 67.059 | 13.469    | 2.511 | 2.575 |
| Type 2    | 637.551 | 27.710    | 7.506 | 11.951 |
| Type 3    | 1087.717 | 28.379    | 10.236 | 15.209 |

To find out the performance of ABO, we will do Friedman test on experiment result. Table 4 shows the results of the Friedman test on the objective function (makespan) and the computational time.

Table 4. Friedman test for makespan and computational time

| Method       | Makespan | Computational time |
|--------------|----------|--------------------|
| **Mean rank**|          |                    |
| Exact Solution| 2.83     | -                  |
| ABO          | 2.83     | 4.00               |
| Hybrid GA    | 2.83     | 3.00               |
| PSO          | 2.83     | 1.00               |
| CSA          | 3.67     | 2.00               |
| N            | 3        | 3                  |
| Chi-Square   | 4.000    | 9.000              |
| df           | 4        | 3                  |
| Asymp. Sig.  | 0.406    | 0.029              |

Friedman test result has shown a significant difference in the solutions produced by ABO and comparison methods. ABO has the optimal solution with the same mean rank as the exact solution,
Hybrid GA and PSO. But in computational time, Friedman test showed ABO has the longest computational time.

4. Conclusions
For solving the Flow Shop Scheduling Problem (FSP) we can use the exact method, heuristic or meta-heuristic method. African Buffalo Optimization (ABO) algorithm has shown better results in minimizing makespan than the Crow search algorithm (CSA). ABO will be an alternative for solving FSP, but the computation time of ABO is slower than other meta-heuristic methods. So for the future, the models can be extended in the NP-hard problem. But to speed up the calculation time, it is necessary to improve the ABO algorithm, for example by hybridizing with other meta-heuristics methods or improvement in the ABO step.

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