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CONTENTS

SESSION 1: PROCESS PLANNING, OPTIMIZATION, LOGISTICS AND INTERNET TECHNOLOGIES IN PRODUCTION ENGINEERING

SESSION 2: MATERIALS, METAL FORMING, CASTING AND WELDING

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THE ARITHMETIC OPTIMIZATION ALGORITHM FOR MULTI-OBJECTIVE MOBILE ROBOT SCHEDULING

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Abstract: *In recent years, metaheuristic algorithms have become increasingly advantageous for solving many real-world optimization-based engineering tasks. Integrated process planning and scheduling of machine tools and mobile robots utilized for transportation tasks in a manufacturing environment represents one such task. Since the number of solutions increases exponentially with the addition of either parts, machines, or robots, this task belongs to a group of NP-hard problems. Therefore, for its successful resolution, it is essential to use efficient algorithms that are able to explore vast solution space and provide optimal solutions. In this paper, we propose an algorithm for solving integrated scheduling of machine tools and mobile robots based on a novel arithmetic metaheuristic optimization. The arithmetic optimization algorithm belongs to a group of stochastic population-based algorithms inspired by arithmetic mathematical operations. The main advantage of the proposed algorithm is in a well-suited balance between exploration and exploitation phases that are appropriate for extremely hard multi-objective optimization. A multi-objective metric is utilized to evaluate obtained Pareto front solutions in terms of the exploration capabilities in the solution space. The proposed algorithm is compared with two other state-of-the-art metaheuristic algorithms. The experimental evaluation is carried out on 20 benchmark problems, and the results show the advantages of the proposed algorithm.*

Keywords: *multi-objective optimization, metaheuristic algorithms, mobile robots, machine tools, scheduling*

1. INTRODUCTION

Contemporary manufacturing systems, inspired by the Industry 4.0 paradigm, tend to maximize the flexibility of the production process, all while maintaining high levels of efficiency. These conflicting criteria need to be balanced to satisfy the highly diversified customer needs while meeting all necessary time requirements. For these reasons, we propose methodology for integrated process planning and scheduling of both machine tools and transportation vehicles utilized for part manipulation. Multi-objective scheduling enables decision-makers in top management level to select a manufacturing schedule with the optimal ratio of different optimization criteria that best fit current manufacturing needs. The result of the optimization process is a set of optimal schedules represented as a Pareto front that can be directly utilized for tactical planning.

The metaheuristic population-based algorithms provide efficiency in exploring the search space, straightforward implementation, and low probability of local optima entrapment. Therefore, they have become extensively used to solve real-world mechanical engineering optimization problems [1]. Since integrated process planning and scheduling with mobile robot-related constraints represent the discrete high dimensional optimization problem (shown to be NP-hard), the optimal solution cannot be obtained using standard optimization algorithms. Therefore, this paper proposes metrology for multi-objective scheduling of manufacturing entities based on metaheuristic Arithmetic Optimization Algorithm (AOA) [2]. The initial exploration-exploitation ratio of the AOA algorithm is heavily tilted on the exploitation side. However, for the problem at hand, the exploration is a more significant phase; therefore, we propose an improvement to the AOA algorithm that enhances the exploration phase. Moreover, implementing the AOA algorithm enables fast rescheduling with different multi-objective criteria if a new part enters the manufacturing system or some other disturbance occurs.

2. IMPLEMENTATIONS OF AOA ALGORITHM – A STATE-OF-THE-ART REVIEW

Since its emergence in 2021, AOA [2] has become increasingly popular for solving many engineering problems [3]. Therefore, many authors have proposed different AOA improvements based on the problem at hand. AOA [4] was implemented for solving discrete structural problems, where the solution update strategy was improved to search around the current position of each individual in the search space instead of around the leader. Moreover, the parameter MOP_i that defines the distance each individual moves in the search space has also been modified, and a stochastic element has been added. The hybrid AOA algorithm used for many engineering optimization problems is presented in [5]. The authors utilized a specific initialization strategy to spread the initial solutions in the search space and, therefore, improved AOA's exploration capability. Moreover, the convergence is improved by incorporating an optimal neighborhood strategy. Lastly, the AOA is hybridized with a crossover algorithm, which boosts optimization accuracy for complex problems. The development of multi-objective AOA algorithm utilized for solving real-world optimization problems is proposed in [6]. The algorithm is implemented with non-dominance sorting crowding distance, and the evaluation is performed based on five multi-objective metrics and non-parametric statistical significance testing. The experimental results show the advantages of AOA compared to the other four metaheuristic algorithms. Another interesting approach for improving the AOA algorithm is with chaotic maps [7]. Different chaotic maps were implemented to generate random numbers for two AOA parameters. The novel improved AOA was tested on benchmark function, as well as on four engineering design problems. The AOA with Circle and Piecewise maps have shown the best overall results for engineering design problems. Improving AOA exploration by integrating a forced switching mechanism is proposed in [8]. The proposed mechanism forces the solutions to significantly change their position in the search space if the fitness function value has not changed for a predefined number of iterations. The improved AOA was tested on different problems such as training of multi-layer perceptron, including various benchmark functions and real-world engineering applications.

Different from these approaches, we improve AOA algorithm by extending the range of the MOA_i parameter, providing 100% exploration in the beginning of optimization, and ensuring that only exploitation occurs in the last few iterations.

3. ARITHMETIC OPTIMIZATION ALGORITHM

Arithmetic Optimization Algorithm (AOA) represents the newly proposed metaheuristic algorithm that is often utilized in engineering optimization problems. AOA is classified as a nature-inspired metaheuristic algorithm belonging to a physics-based group. Its main optimization principle is based on four arithmetic mathematical operations: addition, subtraction, multiplication, and division. AOA also belongs to a group of population-based algorithms in which the candidate solutions interact in a certain way to obtain the optimal solution to an optimization problem.

The entire population of candidate solutions is defined with a matrix $\boldsymbol{X}$ (Eq. 1), where the rows represent individual solutions, while the columns contain different solution parameters:

$$\boldsymbol{X} = \begin{bmatrix} x_{1,1} & \cdots & x_{1,n} \\ \vdots & \ddots & \vdots \\ x_{N,1} & \cdots & x_{N,n} \end{bmatrix}, \quad (1)$$

where N represents the number of individual solutions, and n is the number of solution parameters. There are two distinct phases in the AOA algorithm: exploration and exploitation. In the exploration phase which is present in the early stages of the optimization process, the algorithm explores the vast solution spaces, trying to find suitable candidate solutions. Within the exploitation phase, already found suitable solutions are utilized to find even better solutions, which are close by in the search space. The exploration phase of AOA algorithm is defined with multiplication and division, while exploitation is defined with addition and subtraction. The hyper-parameter that defines if each individual solution parameter will undergo exploration or exploitation is $\boldsymbol{MOA_i}$ (Eq. 2):

$$\boldsymbol{MOA}_i = M\_min + i\left(\frac{M\_max - M\_min}{G}\right), \quad (2)$$

where $i=1,\dots,G$ is the current iteration number, is the maximal number of iterations, M_min and M_max are the minimal and maximal values for parameter $\boldsymbol{MOA_i}$. Moreover, two additional random numbers (r_1 and r_2 ranging between 0 and 1 with uniform distribution) are utilized to determine which phase is selected and which arithmetic operation is performed, which is defined with the algorithm shown in Figure 1. Initial values for the M_max and M_min, are 1.0 and 0.2.

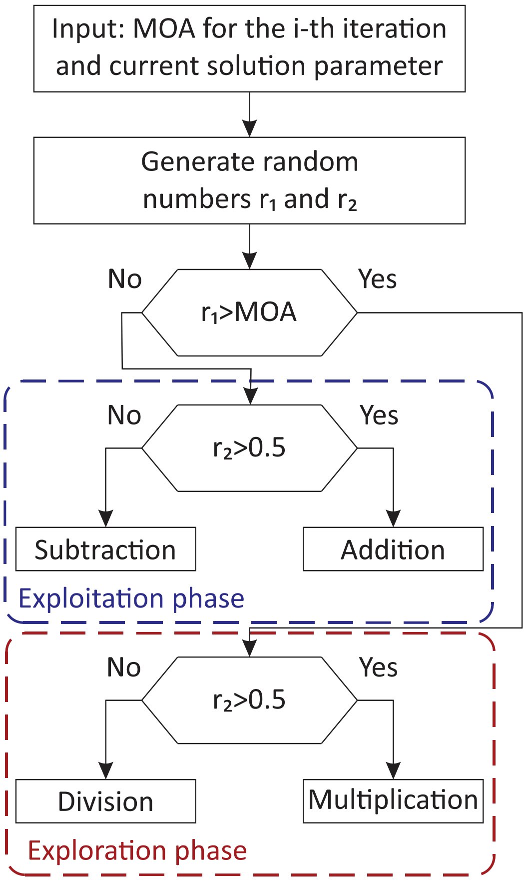


Figure 1. Algorithm for exploration/exploitation selection.

Therefore, the exploration and exploitation phases can occur at any time during optimization. However, it is not desirable that the best solution can change its position in the last few iterations based on stochastic nature. Consequently, the first improvement to the AOA algorithm is the change in the value of M_max from 1 to 1.2, enabling only the exploitation to be performed for the last 14% of iterations, and changing the value of M_min from 0.2 to -0.2, enabling only exploration in the first 14% of the iterations.

The parameter $\boldsymbol{MOP_i}$ (Eq. 3) is used to define the distance each solution moves from the leader throughout the optimization:

$$\boldsymbol{MOP}_i = 1 - \frac{i^{1/\alpha}}{G^{1/\alpha}}, \; i = 1,\dots,G, \quad (3)$$

where $\alpha=5$ represents the sensitivity parameter. Finally, each solution parameter in the population is updated according to one of the following Eqs. (4)-(7):

$$x_{k,j}(i+1) = \frac{xbest_j}{(\boldsymbol{MOP}_i + \varepsilon)(ub_j - lb_j)\mu + lb_j}, \quad (4)$$

$$x_{k,j}\left(i+1\right)=xbest_j\cdot\left(\boldsymbol{MOP}_i\left(ub_j-lb_j\right)\mu+lb_j\right), \quad (5)$$

$$x_{k,j}\left(i+1\right)=xbest_j-\left(\boldsymbol{MOP}_i\left(ub_j-lb_j\right)\mu+lb_j\right), \quad (6)$$

$$x_{k,j}\left(i+1\right)=xbest_j+\left(\boldsymbol{MOP}_i\left(ub_j-lb_j\right)\mu+lb_j\right), \quad (7)$$

where $xbest$ is a leader or the best individual, and $xbest_j$ is lider's j-th solution parameter, ub and lb represent the upper and lower bound of solution parameter space, ε is a small number, and μ=0.499. Specific mechanisms need to be added in order to employ the AOA algorithm in multi-objective optimization. Firstly, the non-dominance sorting is employed to determine the optimal solutions in a population. Afterwards, these solutions are added to the Pareto front, and all of them are considered leaders. The method for the leader selection in Eqs. (4)-(7) is a random strategy proposed in [9]. Four strings, including process plan, schedule, machine, and tool, represent one individual solution adopted from [10]. The entire algorithm for AOA in integrated process planning and scheduling of machine tools and mobile robot is presented in Table 1.

EXPERIMENTAL RESULTS

Experiments were performed on the dataset containing 20 problems with different number of jobs and operations [10]. All the jobs have process, sequence, machine, and tool flexibility. Two multi-objective fitness functions are selected for evaluation of the proposed algorithm. The first is focused on the mobile robot performance, with robot finishing and waiting time being the criteria for optimization. Meanwhile, the second multi-objective fitness function is designed with total flow time and transportation time. Mathematical formulation for all single-objective fitness functions can be found in [9].

The metric used to differentiate between the convergence properties of the analyzed algorithms is Inverted Generational Distance (IGD) [11]. All three algorithms, Whale optimization algorithm (WOA), AOA, and Particle Swarm Optimization (PSO), have been run ten times on each problem with precisely the same initial populations.

Table 1. Multi-objective AOA algorithm.

```
Input: μ; α; G=300; N=300 (population size); dataset for manufacturing system
Initialize random initial solutions for the entire population
while i <= G (i++)
    Calculate fitness function for each individual
    Perform Pareto dominance sorting, leader selection
    Calculate value for MOA_i (Eq. 2) and MOP_i (Eq. 3)
    for #1 every individual
        for #2 every solution parameter
            generate random numbers r1 and r2
            if #3 r1>MOA_i
                if #4 r2>0.5
                    Update parameter according to (Eq. 5)
                else #4
                    Update parameter according to (Eq. 4)
                end #4
            else #3
                if #5 r2>0.5
                    Update parameter according to (Eq. 7)
                else #5
                    Update parameter according to (Eq. 6)
                end #5
            end #3
        end #2
    end #1
```

25:	Optimal Pareto front, save results

Table 2. The best and mean achieved results for each problem, IGD metric, fitness function #1.

Pr.	Best			Mean		
	WOA	AOA	PSO	WOA	AOA	PSO
1.	**0.175**	0.182	0.388	0.403	**0.365**	0.552
2.	0.228	**0.009**	0.475	0.514	**0.432**	0.803
3.	0.175	**0.127**	0.195	0.215	**0.180**	0.291
4.	0.401	**0.011**	0.442	0.560	**0.386**	0.587
5.	**0.035**	0.093	0.166	0.191	**0.180**	0.285
6.	0.221	**0.121**	0.303	0.386	**0.226**	0.439
7.	0.500	**0.159**	0.382	0.571	**0.443**	0.578
8.	0.356	**0.106**	0.525	0.589	**0.362**	0.738
9.	**0.008**	0.188	0.472	0.499	**0.466**	0.641
10.	0.218	**0.118**	0.325	0.478	**0.311**	0.679
11.	0.155	**0.101**	0.451	0.358	**0.292**	0.610
12.	0.221	**0.176**	0.492	**0.423**	0.476	0.733
13.	**0**	0.229	0.419	0.415	**0.357**	0.610
14.	**0**	0.385	0.945	**0.513**	0.686	1.263
15.	**0.080**	0.219	0.414	**0.332**	0.347	0.712
16.	0.231	**0.064**	0.562	0.506	**0.424**	0.855
17.	0.063	**0**	0.609	0.571	**0.235**	0.902
18.	**0**	0.133	0.326	**0.293**	0.348	0.546
19.	**0**	0.295	0.434	**0.451**	0.531	0.684
20.	0.165	**0.134**	0.402	0.362	**0.253**	0.526

The quantitative results for multi-objective fitness function #1 can be seen in Table 2. The AOA algorithm achieves 15/20 mean best results and 12/20 best results on the 20-problem benchmark, making it the best algorithm overall.

Furthermore, to evaluate how many times algorithms achieved the best result compared on each individual run (since the initial populations are the same), for all problems and two fitness functions, the histogram in Figure 2 is shown. With this comparison, the stochastic elements are negated since randomly generated elements can be beneficial to some algorithms.

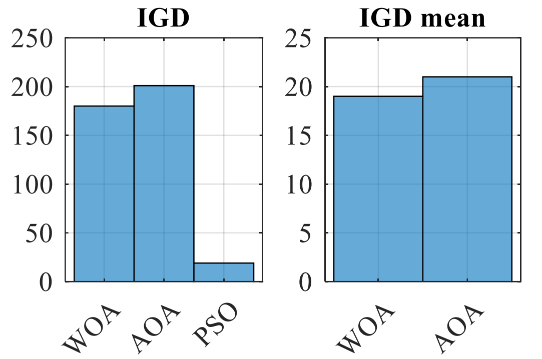
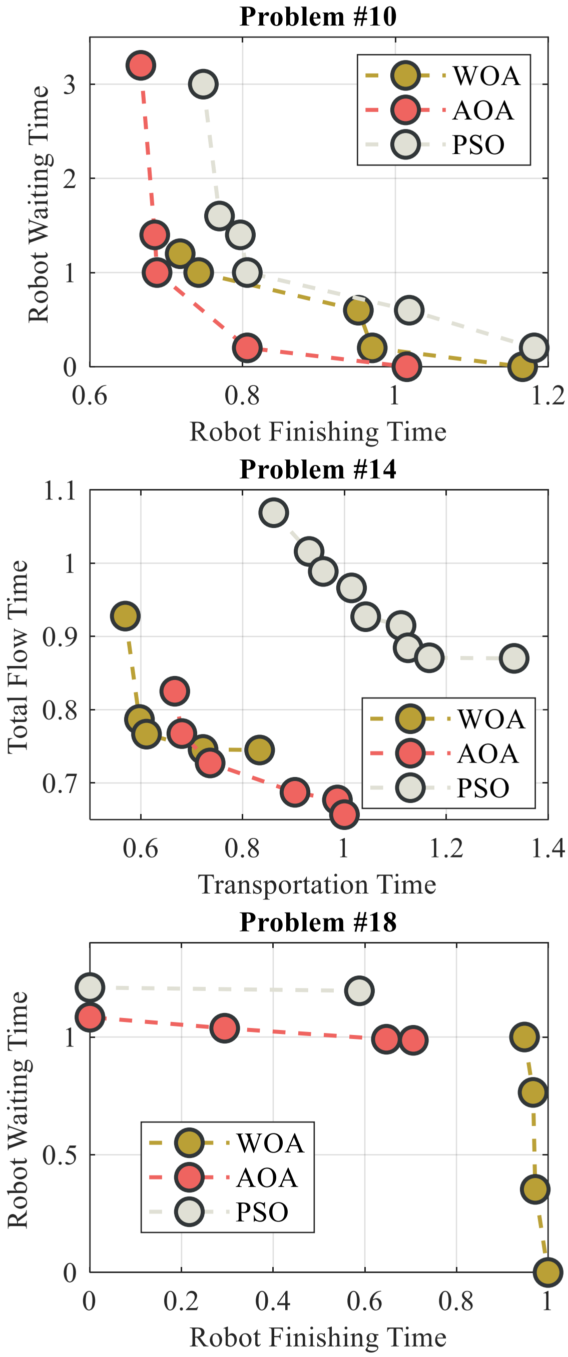


Figure 2. Histogram of results for all runs.



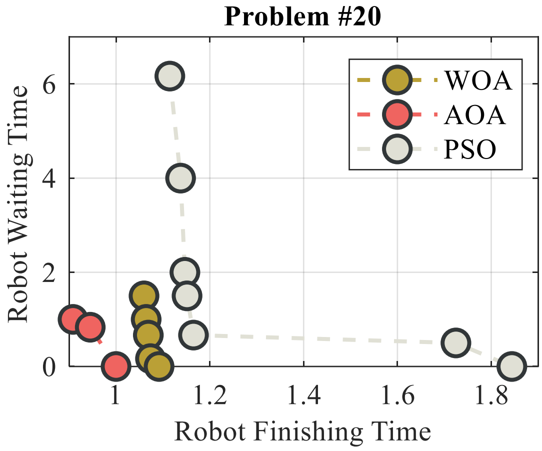


Figure 3. Pareto fronts for selected problems.

As it can be seen from Figure 3, AOA achieves the best Pareto fronts, which shows its advantages even in qualitative evaluation. Moreover, the diagram for problem #18 in Figure 3 shows that AOA focuses significantly on robot finishing time, while WOA optimizes primarily for the robot waiting time fitness function.

CONCLUSION

In this paper, we presented the methodology for multi-objective optimization of the manufacturing schedules with mobile robot utilized for the transportation tasks. The optimal schedule is obtained by employing a metaheuristic Arithmetic Optimization Algorithm (AOA). AOA is compared to two state-of-the-art optimization algorithms on a benchmark with 20 problems and two multi-objective fitness functions. Experimental results show that AOA achieves better results, both in quantitative and qualitative analysis. Future research directions include the further analysis of methodologies capable of improving the AOA algorithm.

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