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An improved MOEA/D algorithm for solving the dual-resource constrained flexible job shop scheduling problem

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***Abstract*—In the manufacturing sector of customized production environments, multi-skilled workers play a pivotal role as they can swiftly adapt their work tasks to accommodate the unique needs of various products. Nevertheless, frequent shifts in job assignments not only hinder production efficiency but also place additional strain on the workers.Thus, this paper investigates a dual-resource constrained flexible job shop scheduling problem with limited multi-skilled workers. And a mathematic programming model is established aiming to minimize both completion time and the maximum workload of the workers. To address the proposed model, an improved multi-objective evolutionary algorithm based on decomposition with Q-learning enhancements (Q-MOEA/D) is proposed. In Q-MOEA/D, an adaptive strategy based on Q-learning is introduced to enhance the convergence speed of the algorithm. Additionally, a neighborhood micro-population search strategy is designed to enhance exploration and exploitation capabilities. Finally, the method's efficacy and superiority are affirmed through extensive experiments involving a significant number of test cases.**

Keywords-Dual-resource constrained; flexible job shop scheduling problem; multi-skilled workers; Q-Learning ; MOEA/D

I. INTRODUCTION

Modern production management has integrated workforce-related constraints and objectives into its planning processes, recognizing them as crucial to contemporary production philosophy. In many manufacturing scenarios, specific machines require the skilled workers with targeted capabilities, which are often limited. Additionally, when formulating production plans, it is imperative to fully consider the compatibility between the capabilities of skilled workers and the machines, as well as the synergistic effects between the two. Therefore, for flexible job shop scheduling problem (FJSP) considering worker resources, i.e., dual-resource constrained FJSP (DRCFJSP) is more challenging.

Mueller & Kress [1] incorporated labor ability differences into the flexible job shop scheduling model. Peng et al.[2] recognized that worker efficiency is not static and unchanging, but is profoundly affected by their learning and memory abilities. In addition, the diversity of product demand puts higher demands on the flexibility and adaptability of skilled workers. Not only do they need to master a variety of skills, they also need to be able to quickly adjust their work according to production needs in order to cope with the production process and specific requirements of different products. However, frequent job changes not only elevate workers' time consumption in moving and reconfiguring equipment, which directly reduces productivity, but also imposes additional psychological burdens on workers, such as fatigue and boredom, which in turn affects their motivation and overall productivity.Sekkal et al.[3], extended the perspective of the study to the subjective perception level of workers, especially their fatigue status. Shi et al.[4] pointed out that performing repetitive work over a long period of time may increase workers' boredom. Zhang et al. [5] considered the impact of labor differences and the need for workpiece transportation.

The above studies treat workers as interchangeable task executors, overlooking the necessity of task-switching adjustments. In reality, workers must rearrange workspaces and prepare for new tasks, affecting production efficiency and workload. This paper investigates the flexible job scheduling problem under the dual resource constraint of considering limited multi-skilled workers and their transfer(DRCFJSP-LMWT), aiming to minimize both completion time and the maximum workload of workers simultaneously. A MOEA/D algorithm based on Q-learning improvements is designed for this problem to provide effective Pareto front solutions.

The paper is organized as follows: Section II gives a description of the current problem as well as the mathematical model; Section III describes in detail the detailed procedure of the proposed Q-MOEA/D algorithm; then the computational results obtained are analyzed in Section IV; and finally, conclusions as well as some future research directions are provided in Section V.

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II. PROBLEM FORMULATION

A. .Problem Description

The DRCFJSP-LMWT can be defined as follows: a set of jobs , a set of machines, and a set of workers. Each job has a set of operations that must be executed sequentially, and for each operation there is a set of machines that can be selected to and assigned a non-empty set of machines that can be operated to carry out the execution of the job by a set of qualified workers , in addition to the operation time of each operation depends on the selected machines and assigned workers. Transportation time includes the adjustment time needed for a worker before and after moving between different machines, as well as the time required to complete tasks when the job is transferred between different machines. Setup time is necessary when consecutively processing two distinct jobs on the same machine. To formulate this DRCFJSP-LMWT problem, the corresponding assumptions are as follows:

(1) All jobs, machines, and workers are available at time zero.

(2) There is no waiting time for the transfer of jobs and workers.

(3) Each process is executed in strict priority order between operations.

(4) Each worker can only operate one machine at a time.

(5) Each machine can process only one job at a time.

(6) Each operation will not be interrupted during execution until it is completed.

B. Mathematical Model

In order to describe the considered problem in terms of a mathematical model, some symbols are defined in this paper, as shown in Table I.

TABLE I. SYMBOLS DESCRIPTION

Symbols	Description
n	Total number of operations
q	Total number of machines
v	Total number of workers
i,k	Job index
m,e	Machine index
j,l	Operation index
w	Worker index
J	Job set
h_i	Total number of operations for J_i
$G_{ij}^{m,w}$	Machines for optional processing of the j_{th} operation of J_i and their corresponding assignable qualified workers
$O_{i,j}$	The j_{th} Operation of Job J_i
$p_{ij}^{m,w}$	Processing time of $O_{i,j}$ on processed by W^w
$TT_{m,e}$	Transportation time of workers or operations from M^m to M^e
$st_{ij}^{m,w}$	$O_{i,j}$ Setup time for processing by W^w on M^m
Ps_{ij}	Continuous decision variables, $O_{i,j}$ actual operating time after selecting the machine and worker configuration, consists of operating time and setup time
C_i	Completion time for assignment J_i
WP_w	Total working time of W^w
$y_{ij}^{m,w}$	binary variables;1 if $O_{i,j}$ chooses M^m and W^w ,and 0 otherwise
$a_{ij,\mathrm{kl}}^{m}$	binary variables;1 if $O_{i,j}$ is processed in M^m before $O_{k,l}$, and 0 otherwise
$b_{ij,\mathrm{kl}}^{w}$	binary variables;1 if $O_{i,j}$ is processed by W^w before $O_{k,l}$, and 0 otherwise
ST_{ij}	binary variables;1 if $O_{i,j}$ needs to be set before execution, and 0 otherwise
t_{ij}	Continuous decision variables, start time of $O_{i,j}$ execution
c_{ij}	Continuous decision variables, end time of $O_{i,j}$ execution
TR_{ij}	Continuous decision variables, transportation time required before the operation performed by job
$TRW_{ij,kl}^{w}$	Continuous decision variables, the transfer time required for W^w to perform two neighboring $O_{i,j}$, $O_{k,l}$ successively

Based on the above notation, this paper develops a mixed integer linear programming model for the problem under study.

$$\min : WP_{\max} \geq WP_w \tag{1}$$

$$\min : C_{max} \geq c_{ih_j} \tag{2}$$

$$\begin{aligned} WP_w = & \sum_{m=1}^{q}\sum_{i=1}^{n}\sum_{j=1}^{h_i} y_{ij}^{m,w} \times p_{ij}^{m,w} + \sum_{m=1}^{q}((1-ST_{ij}) \times y_{ij}^{m,w} \times st_{ij}^{m,w}) \\ & + \sum_{k}^{n}\sum_{l}^{h_i}\sum_{i}^{n}\sum_{j}^{h_i} TRW_{ij,kl}^{w}, w \in W; \end{aligned} \tag{3}$$

$$\begin{aligned} & \mathrm{TRW}_{ij,kl}^{w} = \sum_{m=1}^{q}\sum_{e=1}^{q}(b_{ij,kl} \times y_{ij}^{m,w} \times y_{kl}^{e,w} \times TT_{m,e}), \\ & i,k = 1,2,3\ldots,n;\ j = 1,2,3\ldots,h_i;\ l = 1,2,3\ldots,h_k;\ \forall w \in W \end{aligned} \tag{4}$$

$$\begin{aligned} & ST_{ij} = 1 - \sum_{m=1}^{q}(\sum_{w=1}^{v} y_{ij}^{m,w} \times \sum_{w=1}^{v} y_{i(j-1)}^{m,w}), \\ & i = 1,2,3\ldots,n;\ j = 2,3\ldots,h_i; \end{aligned} \tag{5}$$

$$Ps_{ij} = \sum_{m=1}^{q}\sum_{w=1}^{v}(y_{ij}^{m,w} \times p_{ij}^{m,w}) + \sum_{m=1}^{q}\sum_{w=1}^{v}(ST_{ij} \times y_{ij}^{m,w} \times st_{ij}^{m,w}), \quad i = 1,2,3...,n;\ j = 1,2,3...,h_i; \tag{6}$$

$$\mathrm{TR}_{i,j} = \sum_{e=1}^{q}\sum_{m=1}^{q}(\sum_{w} y_{ij}^{m,w} \times \sum_{w} y_{i(j-1)}^{e,w} \times TT_{m,e}), \quad i,k = 1,2,3...,n;\ j,l = 1,2,3...,h_i; \tag{7}$$

$$t_{ij} + Ps_{ij} = c_{ij}, \quad i = 1,2,3...,n;\ j = 1,2,3...,h_i; \tag{8}$$

$$c_{ij} + TR_{i,j} \le t_{i(j+1)}, \quad i = 1,2,3...,n;\ j = 1,2,3...,h_i - 1; \tag{9}$$

$$t_{ij} + Ps_{ij} + \sum_{w=1}^{v}\mathrm{TRW}_{ij,kl}^{w} \le t_{kl} + L(1 - b_{ij,kl}^{w}) \quad i,k = 1,2,3...,n;\ j = 1,2,3...,h_i; l = 1,2,3...,h_k; \forall m \in M; \tag{10}$$

$$t_{ij} + Ps_{ij} \le t_{kl} + L(1 - a_{ij,kl}^{m}), \quad i,k = 1,2,3...,n;\ j = 1,2,3...,h_i; l = 1,2,3...,h_k; \forall m \in M; \tag{11}$$

$$y_{ij}^{m,w} \le G_{ij}^{m,w}, i = 1,2,3...,n; \quad j = 1,2,3...,h_i; \forall m \in M, \forall w \in W; \tag{12}$$

Equations (1) and (2) denote that optimization objectives are minimum maximum completion time as well as minimum maximum worker working time. Equation (3) denotes the working time of each worker, which consists of processing time, setup time and transition time. Equations (4) denote the transfer time required for each worker to perform two adjacent tasks. Equation (5) denotes that no setup time is required when the job is processed on the same machine before and after the job. Equation (6) denotes that time actually required to be spent for each operation as the operation time plus the setup time. Equation (7) denotes that the transportation time required for each operation before it is performed. Equation (8) denotes the end time for each operation to be the start time plus the actual machining time. Equation (9) denotes that the next operation in the same job to start machining only after the preceding operation has been finished and transported to the relevant machine. Equation (10) denotes that two successive operations performed by the same worker can start machining only if the current operation completes the previous operation and the worker completes the transfer. Equation (11) denotes that two successive operations machined on the same machine can start machining only if the current operation completes the previous operation. Equation (12) denotes that the selection of the machine and the assignment of the qualified workers are correct for each operation.

III. THE PROPOSED Q-MOEA/D ALGORITHM

A. Q-MOEA/D Algorithm Description

To address the DRCFJSP-LMWT problem studied in the research, a novel Multi-Objective Evolutionary Algorithm based on Decomposition with Q-Learning Initialization (Q-MOEA/D) is proposed. The overall process is described as follows: Firstly, initialize the parameters, where the weight vectors determine the optimization direction of each sub-problem. The solution set of each sub-problem forms a micro-population, and the optimization direction of these micro-populations is determined by their corresponding weight vectors. The generation of weight vectors uses a simple grid point design method. Subsequently, utilize Q-learning to adaptively explore the solution space and initialize the population (API-Q). Then, leveraging the hunting mechanism of the grey wolf algorithm, high-quality individuals from different neighborhoods lead and develop through neighborhood microgroups (NMP-HCS). Afterwards, use a scalar function to evaluate the fitness of individuals. In the design of the scalar function, the Q-MOEA/D algorithm ingeniously employs the Tchebycheff aggregation function to construct each sub-problem, which can be described as:

$$Minimize\ \mathrm{g}^{te}(x \mid \lambda^{j}, z^{*}) = \max_{1\le i\le m}\left\{\lambda_i^{j}\left|f_i(x) - z_i^{*}\right|\right\} \tag{13}$$

where m represents the number of optimization objectives, $i = 1,2,...,m$, $\lambda^{j} = \left(\lambda_1^{j}, \lambda_2^{j}, ..., \lambda_m^{j}\right)^T$, $z^{*} = \left(z_1^{*}, z_2^{*}, ..., z_m^{*}\right)^T$ denotes the reference point, z_i^{*} denotes the i_{th} component of the reference point, and $z_i^{*} \le \min\left(f_i(x) \mid x \in \Omega\right)$. The multi-objective problem can be transformed by minimizing each individual objective function $\mathrm{g}^{te}(x \mid \lambda_i, z^{*})$ separately. The strategy of using the best objective value $z = \left(z_1, z_2, ..., z_m\right)^T$ in the population serves as the reference point and updating this reference point generation by generation during the iteration process is adopted.

Subsequently, the set of excellent solutions is saved to an external archive. Eventually, the Q-tables are updated based on these evaluations to complete the iteration of the algorithm.

B. Solution Representation

For the DRCFJSP-LMWT problem, a three-tier encoding scheme has been devised: Operation Sequence Coding (OSC), Machine Assignment Coding (MAC), and Worker Assignment Coding (WAC). OSC determines the order of operations, MAC specifies machine assignments, and WAC outlines worker assignments. By integrating OSC, MAC, and WAC, a feasible solution to the problem can be obtained. Each chromosome's gene count equals the number of operations in the job.

The decoding process involves selecting operations according to the OSC sequence and assigning machines and workers based on MAC and WAC. During scheduling, the completion time of the previous task is first checked, and if conditions are met, the operation is added to the top of the task queue for the corresponding machine and worker. This step is repeated for all operations.

C. Adaptive Population Initialization Based On Q-learning

Three agents are used to generate the encoding of OSC, MAC, and WAC: operation sequence agent (OSA), machine assignment agent (MAA) and worker assignment agent (WAA). A board game is set up to represent the OSA's choice of the order of operations, and the OSA can select pieces based on the current state to determine the order of operations. After determining the OSC part, a MAC is randomly selected from the eligible machine set and then randomly assigned eligible workers to form WAC. The rules for mapping the board are as follows.

(1) The chessboard features a grid of dimensions by , where the width is based on the number of operations, and the height corresponds to the total number of operations.

(2) Chess pieces of the same column but on different layers have sequence requirements, while those in different columns do not have such requirements.

(3) Operations with order constraints are positioned as pieces in the same column of the board.

(4) Operations with order constraints, from the same operation, are placed in the same column, while the previous operation is set in the next row.

According to the mentioned board game, the agent extracts the pieces by observing the bottom row of the board. Thus, in round t, the actions of OSA, MAA and WAA can be defined as:

$$a_t^o = O_{ij} \ \ if \ \ OSA \ picks \ O_{ij} \tag{14}$$

$$a_t^m = M^m, M^m \in M_{ij} \tag{15}$$

$$a_t^w = W^w, W^w \in W_{ij}^m \tag{16}$$

Where i, j is the number of the operation selected by a_{ij}^o and m is the number of the machine selected by a_{ij}^m.

The reward size is based on the likelihood that the genes of the best individuals within the micro-population fall within the distribution. The rewards of OSA, MAA and WAA are defined as follows:

$$r_t^o(i) = \frac{1}{N_j^{sub} \times p_e} \times \sum_{k=1}^{N_j^{sub} \times p_e} s_t(k,i) \tag{17}$$

$$r_t^m(i,j,m) = \frac{1}{N_j^{sub} \times p_e} \times \sum_{k=1}^{N_j^{sub} \times p_e} y_{ij}^m(k) \tag{18}$$

$$r_t^w(i,j,m,w) = \frac{1}{N_j^{sub} \times p_e} \times \sum_{k=1}^{N_j^{sub} \times p_e} y_{ij}^{m,w}(k) \tag{19}$$

where $s_t(k,i)$ denotes whether or not the k_{th} individual OSA chooses the operation of job J_i at round t, $y_{ij}^m(k)$ denotes whether or not the k_{th} individual's $O_{i,j}$ chooses machine M^m, $y_{ij}^{m,w}(k)$ denotes whether or not the k_{th} individual's $O_{i,j}$ chooses machine M^m and worker W^w , and N_j^{sub} denotes the size of the micro-population, $N_j^{sub} = PS / N, j = 1,2,...,N$, p_e denotes the rate of elite individuals, and the top p_e individuals in the population are considered elite based on their fitness ranking.

The Q-table update formula for OSA, MAA and WAA is as follows:

$$Q_o\left(s_t^o,\ a_t^o\right) \leftarrow Q_o\left(s_t^o,\ a_t^o\right) + \alpha \cdot \left(r_{t+1}^o + \gamma \cdot \max_{a^o} Q_o\left(s_{t+1}^o,\ a^o\right) - Q_o\left(s_t^o,\ a_t^o\right)\right) \tag{20}$$

$$Q_m\left(s_t^m,\ a_t^m\right) \leftarrow Q_m\left(s_t^m,\ a_t^m\right) + \alpha \cdot \left(r_{t+1}^m + \gamma \cdot \max_{a^m} Q_m\left(a_{t+1}^o,\ a^m\right) - Q_m\left(s_t^m,\ a_t^m\right)\right) \tag{21}$$

$$Q_w\left(s_t^w,\ a_t^w\right) \leftarrow Q_w\left(s_t^w,\ a_t^w\right) + \alpha \cdot \left(r_{t+1}^w + \gamma \cdot \max_{a^w} Q_w\left(a_{t+1}^o \,\&\, a_{t+1}^m,\ a^w\right) - Q_w\left(s_t^w,\ a_t^w\right)\right) \tag{22}$$

where γ is the discount factor and Q_o、Q_m、Q_w are the Q-tables for OSA, MAA and WAA, respectively.

D. *Neighboring Micro-population Search Strategy*

Because adjacent subproblems share similar solutions, information from them can aid in optimization. Adjacent subpopulations differ slightly in their weight vectors by about $1/H$,where H is a positive integer set according to the size of the problem. . Before and after considering a subpopulation and its neighbors, the leader is chosen from among them. Take α , β and δ wolves as leaders to search for the optimal solution together with ω wolves. An equilibrium B_f factor is also included in the process to prevent the algorithm from experiencing "premature convergence", as shown in Equation (23). When the equilibrium factor $B_f \geq 0.5$, ω wolves cross with the leader as follows.

(1)Produce a random number in the range of 0 to 1, denoted as P_c

(2)When $0 \leq P_c < 1/3$, individual wolves are crossed with individual wolves; when $1/3 \leq P_c < 2/3$, ω-wolf individuals are crossed with β-wolf individuals; and when $2/3 \leq P_c \leq 1$, ω-wolf individuals are crossed with δ-wolf individuals.

When the equilibrium factor $B_f \leq 0.5$, the two-by-two crossover of "ω-wolf" individuals is performed to avoid the algorithm being "immature" in later iterations.

$$B_f = (1 - \frac{t}{MG}) \cdot B_0 \tag{23}$$

where t represents the current iteration, and the parameter B_0 is a random value within the range (0, 1).

The precedence operation crossover is utilized to conduct the crossover operation, guaranteeing the generation of feasible offspring solutions.

IV. Experimental Result

To evaluate the performance of the Q-MOEA/D method, computational tests are conducted using MATLAB 2022b on a computer with the following specifications: an i5-9300 CPU at 2.4 GHz, 16 GB of RAM, and a 64-bit version of Windows 10.

A. *Experimental Setup*

Due to the lack of relevant datasets, this paper adopts two benchmark datasets provided by Mueller et al.: 10 instances (MK1-MK10) from Brandimarte and 6 instances (DP1-DP6) from Dauz-Prado and Paulli. Additionally, information on transportation and setup times is designed and incorporated. To ensure fairness, all algorithms were run for the same number of generations using the same termination conditions, and each algorithm was run 30 times independently for each test sample.

B. Comparison of Algorithms

To validate the feasibility of the improved Q-MOEA/D algorithm, this paper compares it with other classic algorithms and recent algorithms, both classic and cutting-edge, that have also been applied to solve the dual-resource-constrained flexible job shop problem. These algorithms include the Non-dominated Sorting Genetic Algorithm-II (NSGA-II) (Yuan et al. [6], 2021), the Multi-Objective Grey Wolf Optimizer (MOGWO) (Mirjalili et al. [7], 2016), an improved version of MOGWO based on MOEA/D (MOGWO/D)(Xu et al. [8], 2021), and the Multi-Objective Evolutionary Algorithm with Reinforcement Learning (MOEA-RL) (G. Zhang et al. [5], 2024). Among them, NSGA-II and MOGWO are classic algorithms, while MOGWO/D and MOEA-RL are advanced algorithms proposed in recent years. The evaluation employs the Hypervolume (HV) metric, the experimental results are shown in the Table II.

TABLE II. HV RESULTS OF FOUR ALGORITHMS

Instance	Q-MOEA/D	NSGA-II	MOGWO	MOGWO/D	MOEA-RL
MK1	**0.9108**	0.4983	0.1866	0.5075	0.865
MK2	**0.9843**	0.5546	0.2828	0.3593	0.2437
MK3	**0.9668**	0.8131	0.4112	0.4063	0.6488
MK4	**0.936**	0.7287	0.1504	0.3648	0.312
MK5	**0.8321**	0.7899	0.6511	0.2212	0.6239
MK6	**0.9393**	0.8147	0.7184	0.5428	0.6645
MK7	**0.8279**	0.7962	0.5531	0.1278	0.5435
MK8	**0.9214**	0.8839	0.4679	0.3722	0.5953
MK9	**0.9274**	0.9068	0.7224	0.5798	0.952
MK10	**0.8978**	0.7311	0.4873	0.3537	0.6724
DP1	**0.92**	0.7417	0.6538	0.5576	0.8286
DP2	**0.8096**	0.8059	0.5993	0.4736	0.7914
DP3	**0.9542**	0.7245	0.777	0.5485	0.8378
DP4	**0.9291**	0.8142	0.7336	0.6459	0.9023
DP5	**0.9336**	0.5623	0.6552	0.5509	0.7942
DP6	**0.903**	0.8687	0.887	0.6786	0.8853

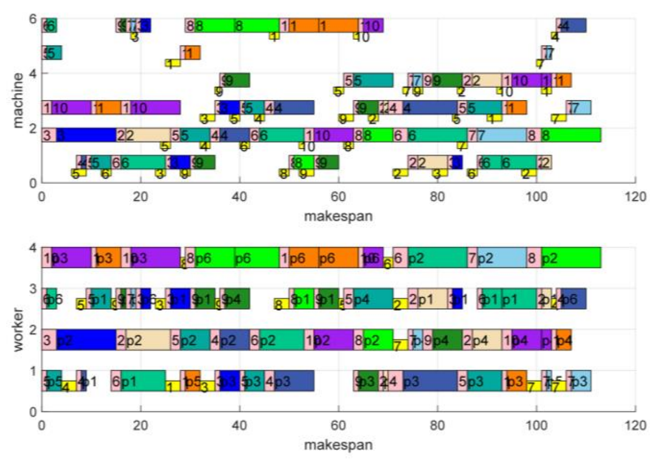

Fig.1 Gantt chart of Q-MOEA/D on MK1 instance

Fig.1 shows the Gantt chart results generated by the Q-MOEA/D algorithm for the MK2 scheduling optimization problem. In the upper part of this figure, the distribution of jobs on the machine is clearly presented: the yellow area represents the transition time, while the pink area represents the setup time, and the other areas with different colors represent the operation time of different jobs, respectively.

The experimental results demonstrate that the Q-MOEA/D algorithm surpasses other multi-objective optimization algorithms in addressing the DRCFJSP-LMWT problem.

V. CONCLUSIONS

This study addresses the flexible job shop scheduling problem by considering a limited number of multi-skilled workers and introduces a comprehensive mathematical model. To optimize this model, the Q-MOEA/D algorithm is proposed. To verify the effectiveness of the proposed algorithm, comparisons were made with other well-known multi-objective optimization algorithms, showing that the proposed algorithm outperforms others in addressing the DRCFJSP-LMWT problem. In the field of production process practices, frequent occurrences of dynamic and uncertain factors include substandard product quality, machinery failures, and personnel allocation changes. Future research will focus on exploring and refining shop floor scheduling strategies and techniques under dynamic and uncertain conditions.

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