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Development of a Multi-Skill Job Rotation Model by Minimizing the Workload Variance

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ABSTRACT

Performing risky or repetitive activities by the operator in each system causes some ergonomic dangers. To reduce these risks, employees must participate in such activities in equal amounts as much as possible. Evaluating this job and finding out how to allocate employees to various tasks during planning time is known as job rotation. In this paper, employees' shift work schedule and job rotation are investigated to reduce costs and consider This study aims to provide an optimal approach to the issue of shift work schedule and job rotation in which the main model is a nonlinear integer programming, and a genetic algorithm is used to solve the mathematical model. To examine the proposed model, the performance of the genetic algorithm is compared with the exact method (GAMS software). The results show that the performance of the genetic algorithm is better than the exact method in significant problems and requires lower computational time.

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1. Introduction

Manpower, equipment and devices, capital and technology and some other factors are among the main factors influencing an organization's emergence, survival and development, of which manpower plays the most important role. When it comes to manpower, factors such as job satisfaction and organizational commitment are raised, which are realized when each employee is assigned to the activities based on their skills. The problems caused by these activities are also minimized. Job satisfaction is the feelings or emotions connecting workers to their jobs (Alvarez-Peregrina et al., 2024). These problems include repetitive tasks and ergonomic damage caused by these activities, leading to fatigue and boredom in the long run. On the other hand, by eliminating these factors, the productivity of the organization can be significantly increased by creating job satisfaction. Job rotation is a method for better organization between existing jobs and manpower, which is increasingly used in manufacturing and service companies. Job rotation's benefits encompass multidimensional skills development (dos Santos Leite et al., 2024; Hakenes & Katolnik, 2017). In this scenario, job rotation serves as a mechanism to prevent employees from continuously engaging in the same task throughout their shift, particularly those with

a high ergonomic risk. Researchers have suggested job rotation as a means to balance physical workload. Experimental research has shown that job rotation effectively lowers the perceived physical strain on workers (Rinaldi et al., 2021).

Job rotation is a method for better organization between existing jobs and manpower, which is increasingly used in manufacturing and service companies. Job rotation serves as an administrative measure to prevent work-related musculoskeletal disorders and offers various benefits in the workplace. These advantages encompass providing training prospects for a diverse and adaptable workforce and eradicating the tedium associated with repetitive tasks. To optimize the effectiveness of job rotation, it's essential to formulate a suitable plan tailored to the workload demands and unique attributes of individual tasks (Yoon et al., 2016). Job rotation offers several benefits for employees and organizations, including reducing boredom, developing skills, increasing employee satisfaction, preventing fatigue, improving company knowledge and fresh perspectives, and increasing employee experience. In various contexts, the definitions of job rotation are diverse and contingent on the intended purpose of employing this strategy. From a managerial perspective, it entails the interchange of employees between tasks and roles demanding distinct skills and responsibilities (Padula et al., 2017). Concerning the control of Musculoskeletal Disorders (MSD) risk, job rotation is characterized as a tactic involving the alternation of workers across tasks featuring varying exposure levels and occupational demands (Howarth et al., 2009). In the dynamic landscape of workforce management, optimizing job rotation strategies has become imperative for enhancing productivity and ensuring the well-being of employees. This article delves into the intriguing realm of job rotation, specifically focusing on workload variance. As organizations increasingly recognize the value of a multi-skilled workforce, the need for a robust job rotation model that not only cultivates diverse skill sets but also minimizes workload disparities has gained prominence.

Multi-Skill Job Rotation is a strategic workforce management approach that systematically guides employees through diverse roles, each demanding distinct skills. The objective is to cultivate a versatile and adaptable workforce by exposing individuals to various organizational tasks and responsibilities. Key characteristics include skill diversification, where employees rotate across roles, fostering a well-rounded workforce (Szwarc et al., 2024); adaptability enhancement by exposing individuals to different organizational functions; promotion of continuous learning throughout one's career; and increased operational flexibility, allowing seamless role transitions. The practice yields advantages such as enhanced operational flexibility, facilitating quick adaptation to changing needs, talent development, fostering a highly skilled and adaptable workforce, and efficient resource allocation based on employee skills and organizational needs (Santos et al., 2017; Santos et al., 2016).

This research presents a mathematical model to minimize the workload variance applied to each employee. This model considers the minimization of the activity cost, the number of vacations, and the employees' individual skills.

2. Literature review

Job rotation involves workers moving between tasks within a job or among various activities to diversify exposure levels. These tasks consist of a mix of actions forming functional operations and activities, which require specific postures or movements for execution (Padula et al., 2017). Job rotation entails placing employees in roles demanding diverse knowledge and skill sets. This organizational approach enhances employees' versatility, fosters career growth, and renders businesses adaptable to challenges like absenteeism, sick leave, or fluctuations in demand. Companies gain a deeper understanding of employees' capabilities and proficiencies through job rotation, assessing their performance across various roles (Eriksson & Ortega, 2006). Diversification in required skills and knowledge prevents monotony (Azizi et al., 2010), reduces absenteeism, boosts career progression, and elevates job satisfaction. Furthermore, the transition between roles and tasks, especially those engaging different muscle groups, mitigates fatigue buildup, consequently lowering the risk of MSDs injuries (Asensio-Cuesta et al., 2012).

Furthermore, job rotation is recognized as a technique for job design that, in addition to enabling workers to acquire job skills from various departments, removes worker fatigue brought on by monotonous work assignments by switching them up. The challenge of these new tasks can rekindle a worker's enthusiasm and boost morale, increasing productivity (Jorgensen et al., 2005). The quality of a person's work experience should be prioritized over quantity while implementing job rotation. The next rotation plan should be set up by organizations based on each employee's learning capacity and adjustment time. Consequently, a high frequency of job rotation might not be optimal; consideration should be given to variables such as the employee's background, learning state, and familiarity with the job (Ho et al., 2009). In short, the objectives of job turnover are shown in Figure 1.

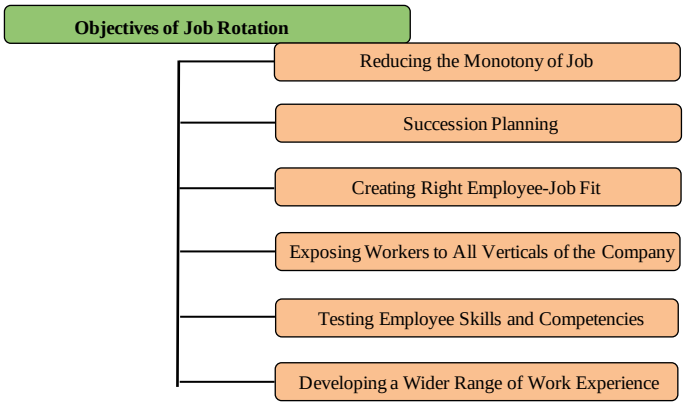


Fig. 1. Objectives of job rotation.

(Assunção et al., 2022) proposed a formulation to help the team leader in an assembly line of the automotive industry to achieve job rotation schedules based on three major criteria: improve diversity, ensure homogeneity, and thus reduce exposure level. The formulation relied on a genetic algorithm that

took into consideration the biomechanical risk factors (EAWS), workers' qualifications, and the organizational aspects of the assembly line. (Diego-Mas et al., 2009) proposed a genetic algorithm that allows the planner to achieve job rotation schedules that aim to reduce the risk of musculoskeletal disorders, obtain maximum diversification of the jobs carried out during working hours, and take into account both permanent and temporary disabilities of the workers as well as their preferences. (Bakhshi et al., 2020) presented a mathematical model for allocating people to different jobs and shifting employees between related jobs. This action will reduce the workload of repetitive activities and ergonomic risks at the planned time horizon, and finally, it will increase the organization's efficiency. (Dinler & Işık, 2020) used the ergonomic risk assessment method, which is defined as an efficient evaluation tool of risks inherited by operators' posture positions. Then, with this method, a job rotation scheduling model, which takes into account the operators' capabilities, is developed. The developed mathematical model is applied to an automotive company, and good results are obtained. (Azizi et al., 2010) presented a methodology for job rotation in manufacturing systems that aims to ease employee boredom and exploit rotation intervals' effect on worker's skill learning and forgetting. To this end, a series of formulations are proposed to measure employee's boredom and skill variations during a production horizon. Based on the proposed formulations, a mathematical programming model for job rotation is developed, and a numerical example is provided to illustrate its applications. (Yoon et al., 2016) suggested a job rotation schedule by developing a mathematical model to reduce cumulative workload from the successive use of the same body region. Workload assessment using rapid entire body assessment (REBA) was performed for the model in three automotive assembly lines of chassis, trim, and finishing to identify which body part was exposed to relatively high workloads at workstations. The proposed schedules prevent the exposure to high workloads successively on the same body region and minimize between-worker variance in cumulative daily workload. Whereas some of the workers were successively assigned to high-workload workstations under no job rotation and serial job rotation. (Adem & Dağdeviren, 2021) investigated how the risks of developing HAV-related occupational diseases can be minimized by producing optimal job rotation schedules using ergonomic mathematical models. The proposed models consider both ergonomic and traditional aspects of manufacturing environments. (Mossa et al., 2016) proposed a model that aims to find optimal job rotation schedules in work environments characterized by low-load manual tasks with a high frequency of repetition (e.g. assembly lines). The mixed integer programming model maximizes production rate, jointly reducing and balancing human workloads and ergonomic risk within acceptable limits. (Digiesi et al., 2018) proposed a model for minimizing workers' exposure risk in repetitive manual tasks by balancing the human workloads and reducing the ergonomic risk within acceptable limits for a given production target. Risk and its acceptability are evaluated using the RULA method, according to a mixed integer programming approach. Results show the effectiveness of the model in identifying the optimal job rotation schedules that jointly achieve productivity and ergonomic risk goals. (AlBaiti et al., 2023)

contributed to the existing research by analyzing the problem with linkages among worker skill level, production rates, and vibration exposure. A bi-objective mixed integer linear programming model was employed to optimize both productivity and exposure to hand-arm vibration in the manufacturing workplace. A sensitivity analysis was carried out to examine the impact of key parameters on the trade-off between productivity and vibration exposure. The results demonstrate the model's effectiveness in determining the best job rotation schedules by achieving optimal productivity and vibration exposure for low and medium problem sizes. (Shojaei et al., 2024) developed a multi-objective mathematical scheduling model to optimize the multi-objective flexible job shop scheduling problem concerning the issues of sustainability with reverse flow and job rotation considerations. The first goal of which is to minimize the construction time and the second goal is to minimize the issues related to sustainability. To solve the model, two methods were used: Sensitivity analysis and whale optimization algorithm (WOA) was employed. The results of the implementation of WOA indicate the efficiency of the proposed algorithm, while the findings of the sensitivity analysis also point to the effect of research innovations on the objective functions of the problem.

This study consists of 6 sections; after stating the problem and describing its process, section 3 introduces the assumptions and components of the proposed model. Then, in section 4, the method of solving the model, the parameters of the algorithm and the experimental design values are described. In section 5, the results obtained from solving the model are presented, and in section 6, the conclusions of this study are presented.

3. Definition and modeling of the problem

3.1. Model assumptions

Every worker has a level of skill which is constant during the study time. The number of machines studied is known. The number of employees required for each group is constant. Each worker can only be assigned to machines with the necessary expertise to work on. Every worker is allowed to take r leave. Due to the maintenance process, the devices are not able to operate at the specified time.

3.2. Problem parameters and variables

Z : Workload variance.

E_i : Workload imposed on worker ith.

$\overline{E}$: The average workload for all employees.

I : Number of Employees.

N : Number of available machine sets.

T : The total number of work shifts on a specific planning.

r : The number of days a person is allowed to take a break on a specific planning horizon.

F : The number of shifts that the device is unable to operate due to the maintenance process.

U : The upper limit of the Eq.(9).

h^0 : The number of activities is determined by the level of difficulty in the shift.

h^{00} : The number of activities is determined by the easy level in t shifts.

C_{ijtd} : The variable cost that represents the cost of workload for each worker with each skill level working with the jth machine set in the tth shift on dth day.

$$S_{ijt} = \begin{cases} 1 & \text{If the i}^{th}\text{ worker has the ability to work on the j}^{th}\text{ device, in t}^{th}\text{ shift} \\ 1 & \text{Otherwise} \end{cases}$$

$$X_{ijt} = \begin{cases} 1 & \text{If i}^{th}\text{ worker device assigned to j}^{th}\text{ worker, in t}^{th}\text{ shift} \\ 0 & \text{Otherwise} \end{cases}$$

3.3. Basic model

$$MinZ = \sum_{i}^{I} (E_i - \overline{E})^2 \tag{1}$$

s.t:

$$\sum_{i=1}^{I}\sum_{J=1}^{N} C_{ijt} X_{ijt} \le E_i \qquad \forall i \tag{2}$$

$$\sum_{i=1}^{I}\sum_{j=1}^{N} X_{ijt} \le 1 \qquad \forall i \tag{3}$$

$$\sum_{j=1}^{N}\sum_{t=1}^{T} X_{ijt} \le T - r \qquad \forall i \tag{4}$$

$$\sum_{j=1}^{N}\sum_{t=1}^{T} X_{ijt} \le S_{ijt} \qquad \forall i,t,k \tag{5}$$

$$X_{ijt} + X_{ij(t+1)} \le 1 \qquad \forall j \in (1 \le J \le N) \tag{6}$$

$$\sum_{j=1}^{N}\sum_{t=1}^{T} X_{ijt} \le h^{\circ} \qquad \forall i \tag{7}$$

$$\sum_{j=1}^{N}\sum_{t=1}^{T} X_{ijt} \le h^{\circ\circ} \qquad \forall i \tag{8}$$

$$\frac{\sum_{j}^{N}\sum_{t}^{T} X_{ijt}}{\sum_{j}^{N}\sum_{t}^{T}\sum_{i}^{I} X_{ijt}} \geq U \tag{9}$$

$$\sum_{t=1}^{T}\sum_{i=1}^{I} X_{ijt} \leq T - F \qquad \forall i \tag{10}$$

$$X_{ijt} \in 0 or 1 \quad C_{ijt} \in R \qquad \forall i \tag{11}$$

The problem is the integer type, in which the objective function of Eq.(1) in the minimum type is proposed to minimize the variance of the workload applied to each employee. Eq.(2) is intended to minimize the cost of employee activity. Eq.(3) states that each person is allowed to work with only one device. Eq.(4) allows each person to take the maximum number of leave. With the help of Eq.(5), each person is assigned to a device that has the necessary skills to work with it. Eq.(6)obliges each person not to do the same activity in two consecutive shifts. If we divide all activities into two groups, difficult and easy activities, with the help of Eqs. (7) and (8), each person will be assigned the maximum h^{0} number of hard work and h^{00} easy work in a certain period. Eq.(9) suggests that a person's total activity in a day is less than half of the total activity that a person performs on a given planning time horizon. Eq.(10) shows that each device is not able to operate in certain shifts due to the maintenance and repair process. Finally, Eq.(11) suggests that our main variable (X_{ijt}) is zero-one type, and that the costs of each employee's activity (C_{ijt}) can account for any actual value.

The objective function in Eq.(1) is nonlinear, and the parameter in Eq.(12) is used to change it into a linear model. Eq.(1) is equivalent to Eq.(13), which, by placing y of the Eq.(12), has turned it into a linear model and is shown in Eq.(13).

$$\begin{aligned} & y_i = \left| E_i - \overline{E} \right| \\ & -y_i \leq E_i - \overline{E} \leq y_i \end{aligned} \tag{12}$$

$$\begin{aligned} & MinZ = \sum_{i}^{I} y_i \\ & E_i - \overline{E} \geq -y_i \\ & E_i - \overline{E} \leq y_i \end{aligned} \tag{13}$$

4. Solution method

4.1. Initial information and data

According to the sample problem in the workshop, three workers were installed for four assembly system devices that operated in 10 working periods. In this workshop, the number of authorized courses

for people taking two courses is considered, and each operator can perform a maximum of eight difficult and easy activities in the total work period. Each device can take a repair course during the work period. The U coefficient in Eqs. (4)-(9) is 0.1. In this regard, each person should be able to perform more than 0.1 of the total activities on the assembly line devices during the programming period.

4.2. GAMS software

The proposed mathematical model using numerical data has been investigated using GAMS software. Since the proposed mathematical model of integer programming is correct, the solution obtained by solving the model in GAMS software with Solver CPLEX that is based on the branch and cut method addresses the general optimal answer. A 2.00 GHz T600 processor is used for this purpose.

4.3. Genetic algorithm

The Genetic Algorithm (GA) is a metaheuristic algorithm, and the time required to implement it is much shorter and more efficient than systematic methods. GA is an evolutionary algorithm that simulates the process of natural selection to solve optimization and search problems. It involves creating a population of potential solutions represented as chromosomes, which undergo evolution through selection, crossover, and mutation. The fitness of each solution is evaluated based on an objective function, and the fittest individuals are more likely to be selected for reproduction, passing on their traits to the next generation (Katoch et al., 2021). GAs have gained significant attention in research due to their ability to efficiently explore large solution spaces and find near-optimal solutions (McCall, 2005). Through successive generations, the algorithm explores the solution space, gradually improving the quality of solutions until satisfactory results are obtained. GAs have been applied in various fields, including engineering, medicine, and computer science, to solve complex optimization problems where traditional methods may struggle (Yang, 2021). GAs offer advantages such as parallel processing, robustness, and the ability to handle nonlinear and multi-modal optimization problems. They have been used in diverse applications, such as scheduling, image processing, and data mining, showcasing their versatility and effectiveness (Link & Weuster-Botz, 2011).

In order to implement the genetic algorithm, the possible answers to the problem have been studied in the form of chromosomes. Each of the chromosomes is randomly selected from the initial population and is formed with the help of cross-over and mutation operators for the new generation of chromosomes. Finally, with the help of the Eq. (13), these repetitions are done until the condition of termination is satisfied. In order to implement the GA algorithm in the allocation problem, we perform the necessary coding in the MATLAB environment and compare the results with the model implemented in GAMS. To reach this purpose, 10 samples were examined in the form of three small samples, 3 medium samples, and four large samples for both mathematical models and genetic algorithm models.

The efficiency of GA depends largely on the control of the parameters, the size of the population (Ps), the probability of the cutting operator (Pc), and the probability of the mutation (Pm). In order to

eliminate possible deviations from the initial GA sequences (population) and ensure the strength of the GA, five initial sequences are randomly generated and tested in each experiment for each combination of parameters (8 combinations in total). In order to reduce variance in each of the eight test factors, the initial 5 sequences will remain unchanged. A stronger approach is to randomly generate five problems and randomly select a random sequence for each problem. During the implementation of the GA for each combination of parameters, these initial problems and sequences will remain unchanged. The composition of the parameters for a problem in a certain size is determined in such a way that for each combination of parameters and for each experimental implementation, the minimum observed value for the production time after 300 executions was considered. Then, the average of these values is obtained on four executions; a combination of parameters is selected that has the lowest average production time.

Table 1 shows the two levels of factors examined in the Design of experiments (DOE). In each experiment, the algorithm is repeated 300 times, and it is assumed that after this number of repetitions, the result obtained will be close enough to the optimal answer.

Table 1. DOE factor levels.

	Factors	**Level 1**	**Level 2**	**Level 3**
1	Ps	1000	2000	3000
2	Pc	0.9	0.7	0.5
3	Pm	0.05	0.09	0.07

To select these parameters, which statistical experiments have confirmed, we examined 27 combinations of population size, the cutting operator's probability, and the mutation probability using the Minitab environment. After randomized trials using the Taguchi method, nine experiments were performed. The results of this method show the best values for the parameters in Table 2.

Table 2. Combining the levels of DOE factors.

value	Factors
2000	Ps
0.9	Pc
0.07	Pm

This study has studied small, medium, and large problems. Dimensions of the studied problems: 4 machines and 3 personnel, 8 machines and 6 personnel, 10 machines and 8 personnel, for small size problems; 20 machines and 10 personnel, 30 machines and 12 personnel, 15 personnel and 49 machines, for problematic dimensions. On average, there are 25 personnel and 60 machines, 30 personnel and 80 machines, 35 personnel and 90 machines, 40 personnel and 100 machines for large-scale problems. The planning period is 10 working periods. The coding of the problems to compare the results of the solution using the exact method (GAMS) and the meta-heuristic method (GA) are tabulated in Table 3.

5. Results

The comparison of the results is interpreted by solving the 10 types of problems mentioned below. According to Table 4 and Figure 2, the results of solving the model using GA are close to the final optimal results of the exact solution and are obtained quickly. This suggests that the results of the genetic algorithm are better than the results of GAMS, both in terms of efficiency and resolution time in large problems.

Table 3. Issues designed in small and large sizes.

Code	Problem dimensions	Parameters		
		Manpower	Machine	Work period
1	Small	3	4	10
2	Small	6	8	10
3	Small	8	10	10
4	Medium	10	20	10
5	Medium	12	30	10
6	Medium	49	15	10
7	Large	60	25	10
8	Large	80	30	10
9	Large	90	35	10
10	Large	100	40	10

Table 4. Compare the results of problem-solving with GAMS and GA software

	GAMS results	Solution time	GA Results	Solution time	Results Difference
Problem 1	2.877E-14	10 Sec.	2.877E-14	3 Sec.	0%
Problem 2	14.12 E-10	50 Sec.	14.12 E-10	10 Sec.	0%
Problem 3	26.31 E-8	30 Sec.	27.25 E-8	1 Min.	3.6%
Problem 4	62.44 E-4	10 Sec.	65.25 E-4	2 Min.	4.5%
Problem 5	78.76 E-3	18 Sec.	83.52 E-3	4 Min.	5.7%
Problem 6	134.99 E-3	30 Sec.	144.22 E-3	7 Min.	6.4%
Problem 7	188.68 E-2	50 Sec.	203.54 E-2	10 Min.	7.3%
Problem 8	299.01 E-2	80 Sec.	327.50 E-2	14 Min.	8.7%
Problem 9	375.16 E-1	120 Sec.	412.72 E-1	22 Min.	9.1%
Problem 10	561.88 E-1	180 Sec.	625.70 E-1	30 Min.	10.2%

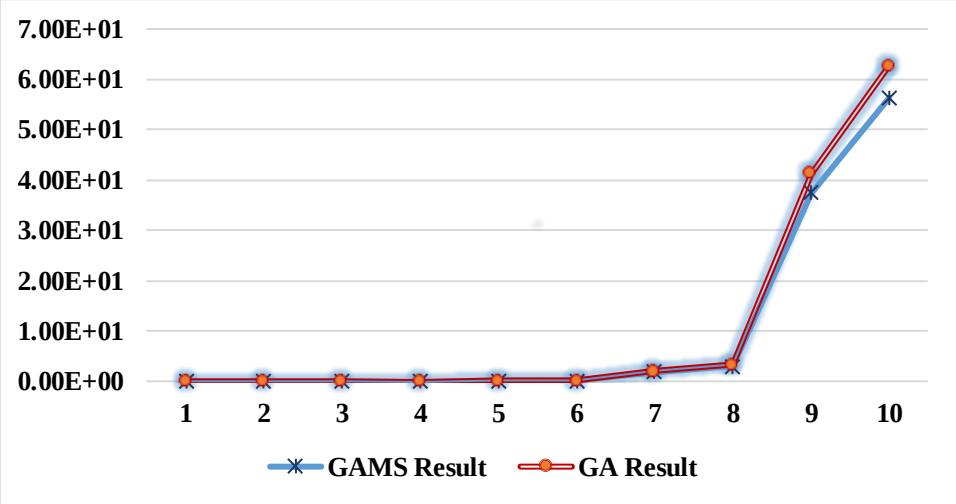


Fig. 2. Comparison of problem-solving results with GAMS and GA software

6. Conclusion

In previous studies, the issue of employee shift schedules and job rotation was examined separately. In order to develop the scheduling of employees and provide an optimization approach, scheduling employees' work shifts and how employees work between workstations is an issue aimed at reducing the variance of employee loading of mathematical modeling employees in this paper. Considering human factors and their effect on employee performance makes it necessary to model these two areas as a model. The shifts allocated to maintenance and repair measures, leave, and employee skill levels affect the workforce's output and, consequently, the organization's efficiency. The presented model is of Complete-NP type, and genetic algorithm and GAMS software are used to solve the model. The results of the experiments showed that the results of the genetic algorithm are better than those of GAMS software in terms of efficiency and solution time in large test problems. Finally, it is recommended that managers use the proposed optimization model to plan and adopt appropriate policies for the organization and employees according to human factors and make the optimal decision. In order to develop the scientific field of employee scheduling, it is recommended that other important engineering and human factors, such as motivation, stress, etc., be analyzed and modeled, and the effect of changing the parameters of each human factor on employee scheduling be studied in future research. In addition, using and comparing other meta-functional and hybrid methods to optimize employee scheduling and workflow issues can be useful.

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