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Fatigue-Equipment Dual-Risk Maintenance Scheduling Optimization for Single-Operator Control Rooms in Baijiu Brewing

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Abstract: To address the problem that maintenance scheduling in less-manned central control rooms of intelligent Baijiu brewing often ignores operator fatigue risk, this study develops a fatigue-aware maintenance-task scheduling model for a single-operator control room in Baijiu brewing. Baijiu brewing is characterized by high temperature, high humidity, and strict fire and explosion-protection requirements, which may accelerate equipment degradation and increase the risks of operator fatigue and human misjudgment. This method converts fatigue state into fatigue-related human-error risk, adopts Weibull conditional failure probability to describe equipment degradation risk, constructs a coupled fatigue-equipment risk model, and establishes a dual-objective scheduling model considering safety risk and response efficiency. Case results show that the dual-risk scheduling scheme achieves a composite objective value of 0.5560, outperforming the fixed-priority scheme (0.6247) and the equipment-risk-driven scheme (0.6511), and reduces high-risk human-machine mismatches from 2 to 0. The results indicate that incorporating fatigue risk improves the safety adaptability of maintenance task arrangements.

1. Introduction

The central control room for intelligent Baijiu brewing serves as a critical node linking the brewing process, equipment condition monitoring, and anomaly disposal decision-making. It undertakes tasks including pit fermentation temperature monitoring, steamer distillation measurement and control, fermented grain conveying control, base liquor quality inspection, safety monitoring, and fire-alarm linkage. With the continuous integration of intelligent sensing, online detection, and centralized control systems, the central control room is shifting from traditional manual inspection and experience-based judgment to a lean-staffed, centralized, and digital duty mode[1]. However, Baijiu brewing features strong process continuity, complex process disturbances, and high safety risks, so fully unmanned operation remains difficult to achieve at present. Key alarm confirmation, anomaly judgment, and disposal decision-making still require operator involvement. Meanwhile, the Baijiu

brewing workshop presents long-term environmental characteristics including high temperature and high humidity, steam and dust, alcohol vapor, flammable media, and confined-space operations. On the one hand, these factors may accelerate the degradation of sensors, pump units, measurement-and-control systems, and safety-monitoring equipment, raising the risk of equipment anomalies and failures; on the other hand, they increase the physiological and cognitive load on duty operators, facilitate fatigue accumulation, and lower the reliability of alarm recognition, anomaly judgment, and response disposal. Since Baijiu production has rigid requirements for fire and explosion prevention, occupational safety, and product quality stability, relevant safety regulations impose clear requirements for combustible gas monitoring, explosion-proof electrical equipment, fire linkage, and anomaly disposal[2]. Therefore, under the lean-staffed-duty scenario of the central control room for intelligent Baijiu brewing, maintenance-task scheduling should focus not only on equipment conditions and task urgency but also on the impact of operator fatigue on the safety of task execution.

Traditional maintenance scheduling usually determines task sequences based on equipment failure probability, task priority, maintenance resources, or economic indicators [3], assuming that operators maintain stable execution capability throughout the scheduling horizon. However, under the single-operator mode, operators must continuously carry out monitoring and disposal tasks, and fatigue accumulates with duty time, impairing the reliability of alarm recognition, judgment, and disposal. Performing highly sensitive tasks under severe fatigue gives rise to high risks. Although some studies have started to consider human error or maintenance personnel reliability [4-5], most still treat human factors as static correction parameters and rarely adopt fatigue state as a time-varying input for scheduling.

In recent years, fatigue detection methods have achieved considerable progress [6], and human-centric PHM also emphasizes the participation of maintenance personnel in decision-making [7]. However, existing fatigue recognition results are mostly applied for warning purposes and have not been fully converted into risk inputs for maintenance task sequencing. Under the single-operator scenario of the Baijiu-brewing central control room, equipment degradation raises the failure probability, whereas operator fatigue lowers the reliability of anomaly recognition and disposal. These two factors jointly influence system-level risk. Therefore, it is necessary to investigate how to convert fatigue recognition results into scheduling variables, so that task sequencing can simultaneously take both equipment state and operator state into account.

This paper presents a case study of fatigue-aware maintenance decision scheduling for a single-operator central control room in intelligent Baijiu brewing. Based on existing fatigue recognition results, operator fatigue is quantified as fatigue-related human error risk. The Weibull conditional failure probability is adopted to characterize equipment degradation risk, and an equipment fatigue sensitivity coefficient is introduced to construct a coupled fatigue-equipment risk model. A dual-objective scheduling model is established with simultaneous consideration of safety risk and response efficiency. With eight types of equipment and twenty maintenance tasks, this study compares three scheduling schemes: fixed-priority scheduling, equipment-risk-driven scheduling, and the proposed fatigue-equipment dual-risk scheduling. This study focuses not on proposing a novel algorithm, but on analyzing the effects of integrating fatigue states into the scheduling model regarding task execution timing, high-sensitivity task avoidance, and safety-efficiency trade-offs.

2. Problem description

The case comprises eight types of central control equipment and twenty maintenance tasks. Let $I = \{1,2,\cdots,m\}$ and $J = \{1,2,\cdots,n\}$ denote the equipment and task sets, respectively, where m =8 and n =20. Each task $j \in J$ is associated with equipment $i(j) \in I$ and has a release time a_j, an

execution duration d_j, a deadline l_j, and a priority weight q_j. Let S_i denote the fatigue sensitivity coefficient of equipment i, which reflects how strongly the reliability of its associated tasks depends on the operator's recognition, judgment, and response. Accordingly, task j uses the coefficient $S_{i(j)}$. Safety-critical or process-critical equipment, such as fire-alarm linkage, dust and steam safety monitoring, and steamer distillation control, is assigned a higher sensitivity level. Equipment whose associated tasks have less stringent response requirements and lower judgment complexity is assigned a lower level. As all selected equipment types are key monitoring objects, this case uses only medium and high sensitivity levels (S_i =2 or 3).

The problem is to determine the execution sequence, start time, and completion time of all tasks assigned to a single operator. Conditions include: one-operator configuration, one task processed at a time, non-preemptive execution, known input parameters, fatigue as a time-segment-based input, and absence of multi-person collaboration, spare-parts constraints, travel-path considerations, and rework activities. The core problem lies in determining the task sequence by jointly considering equipment failure risk, operator fatigue, and response efficiency under single-operator constraints and task-release constraints.

3. Fatigue-equipment risk scheduling model

3.1. Equipment failure risk

A two-parameter Weibull distribution is used to characterize equipment degradation failure risk. The conditional failure probability of equipment i within the execution interval of task j is:

$$P_i(s_j, C_j) = 1 - \exp\left\{-\left[\left(\frac{\tau_i^0 + \frac{C_j}{60}}{\eta_i}\right)^{\beta_i} - \left(\frac{\tau_i^0 + \frac{s_j}{60}}{\eta_i}\right)^{\beta_i}\right]\right\} \tag{1}$$

The failure consequence severity is evaluated from three dimensions: safety impact, quality impact, and production impact, with weights of 0.4, 0.3, and 0.3, respectively:

$$C_i = 0.4C_i^s + 0.3C_i^q + 0.3C_i^p \tag{2}$$

The equipment-side risk is defined as:

$$R_{e,i(j)}(s_j) = P_{i(j)}(s_j, C_j) \cdot C_{i(j)} \tag{3}$$

3.2. Operator fatigue risk

Based on previous operator fatigue recognition experimental results, the fatigue state is taken as an input to the maintenance scheduling model. Referring to the SPAR-H human reliability analysis method [8], the fatigue state is divided into three levels: awake, mild fatigue, and severe fatigue. The corresponding fatigue-related human-error risks are:

$$P_h(t) = \begin{cases} 0.01, & 0 \le F(t) < 0.30 \\ 0.06, & 0.30 \le F(t) < 0.70 \\ 0.18, & 0.70 \le F(t) \le 1.00 \end{cases}$$

In the case, 0–30 min is awake, 30–150 min is mild fatigue, and 150–275 min is severe fatigue.

3.3. Task execution coupled risk

Given the equipment fatigue sensitivity coefficient $S_{i(j)}$ and the fatigue risk amplification coefficient λ, the coupled risk of task j starting at s_j is defined as:

$$R_j(s_j) = R_{e,i(j)}(s_j)[1 + \lambda P_h(s_j) S_{i(j)}] \tag{4}$$

This formula indicates that equipment risk determines the base hazard level, fatigue state affects disposal reliability, and the equipment fatigue sensitivity coefficient characterizes the dependence of different equipment tasks on the human state.

3.4. Scheduling objectives

The safety objective function is:

$$Z_s = \sum_{j \in J} R_j(s_j) \cdot (W_j + d_j) + \kappa \sum_{j \in J} I\left(F(s_j) \geq \theta_H, S_{i(j)} = 3\right) \cdot q_j \tag{5}$$

The efficiency objective function is:

$$Z_e = \sum_{j \in J} q_j \cdot (C_j - a_j) + \mu \sum_{j \in J} q_j \cdot \max(0, C_j - l_j) \tag{6}$$

After 0–1 normalization, the composite objective is constructed as:

$$minZ = \alpha Z_s' + (1 - \alpha) Z_e' \tag{7}$$

A basic genetic algorithm is used as the main solution tool, and a basic ant colony algorithm is used as an auxiliary comparison method[9].

4. Case study

4.1. Scheduling schemes settings

A simulation case is constructed to verify the model. It covers eight types of central control equipment and twenty maintenance tasks. Weibull parameters are specified for each equipment type, while task parameters are set based on alarm response, parameter checking, quality review, and safety inspection activities. A segmented fatigue timeline represents the fatigue state of a single operator during continuous duty. At each scheduling decision, only released and unscheduled tasks are eligible. In Scheme B, the equipment-side risk $R_{e,i(j)}(s_j)$ of each eligible task is calculated by provisionally setting its start time s_j to the current decision time. The four scheduling schemes are summarized in Table 1.

Table 1: Four scheduling schemes

Scheme	Name	Decision Basis
A	Fixed-priority scheduling	Sorted by task priority q_j
B	Equipment-risk-driven scheduling	Sorted by equipment-side risk $R_{e,i(j)}(s_j)$
C	Fatigue-equipment dual-risk scheduling (basic GA)	Minimize the composite objective Z
D	Fatigue-equipment dual-risk scheduling (basic ACO)	Minimize the composite objective Z

Schemes A and B are rule-based baselines, while Schemes C and D are optimization scheduling schemes that incorporate operator fatigue[10]. Scheme C is the main analysis object, and Scheme D is included to examine the sensitivity of the results to the choice of different basic algorithms.

The scheduling results are assessed using six indicators. Table 2 reports the safety objective value, priority-weighted flow time, delay penalty, high-risk human–machine mismatch count, and composite objective value; Figure 1 additionally compares cumulative coupled risk. Cumulative coupled risk, safety objective value, and mismatch count assess safety performance, while weighted flow time and delay penalty assess scheduling efficiency. The composite objective value summarizes their trade-off. A mismatch is counted when a task associated with high-sensitivity equipment $S_{i(j)}$ =3 starts under severe fatigue $F(sj) \geq 0.70$.

4.2. Overall comparison

The main results of the four scheduling schemes are shown in Table 2.

Table 2: Comparison of results for different scheduling schemes.

Scheme	Safety objective value	Priority-weighted flow time	Delay penalty	High-risk mismatch count	Composite objective value
A: Fixed priority	3.1377	6669	2991	2	0.6247
B: Equipment-risk-driven	2.8883	7069	3730	2	0.6511
C: Dual-risk GA	2.1403	6667	3176	0	0.5560
D: Dual-risk ACO	3.5310	7092	3920	2	0.7086

As shown in Table 2, Scheme C yields the lowest composite objective value of 0.5560, outperforming Scheme A (0.6247), Scheme B (0.6511), and Scheme D (0.7086). From the safety perspective, Scheme C reduces the safety objective value to 2.1403 and eliminates high-risk human-machine mismatches, whereas Schemes A and B still produce two such mismatches. From the efficiency perspective, Scheme C also achieves the lowest priority-weighted flow time (6667), which is slightly lower than that of Scheme A (6669) and evidently lower than that of Scheme B (7069). Although its delay penalty is higher than that of Scheme A, it is lower than those of Scheme B and D. This indicates that the proposed dual-risk scheduling scheme improves safety adaptability without incurring excessive response-related losses.

4.3. Multi-indicator comprehensive comparison

The cumulative coupled risk, safety objective value, priority-weighted flow time, delay penalty, high-risk human-machine mismatch count, and composite objective value are normalized using 0–1 normalization.

As shown in Figure 1, Scheme A exhibits certain advantages in flow time and delay penalty. However, it neglects both equipment risk and operator fatigue status, thereby retaining high-risk human-machine mismatches. Scheme B enhances the control of equipment-side risk but fails to consider operator fatigue, resulting in non-optimal safety and composite objective values. By contrast, Scheme C achieves superior performance in terms of safety objective, high-risk human-machine mismatch count, and composite objective value. This demonstrates that the incorporation of operator fatigue enables the model to optimize the matching between high-sensitivity tasks and operator physical conditions. Overall, Scheme D performs worse than Scheme C, indicating that the basic

genetic algorithm is more suitable as the primary solution tool for the scale of the presented case.

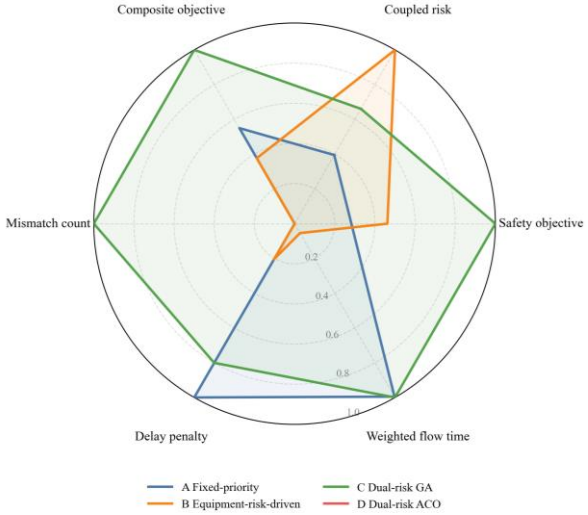


Figure 1: Multi-indicator normalized comparison of the four scheduling schemes.

4.4. Task timing and human-machine matching analysis

Figure 2 compares the four Gantt schedules. Green, yellow, and red indicate awake, mild, and severe fatigue at task start; blue borders mark high-risk mismatches.

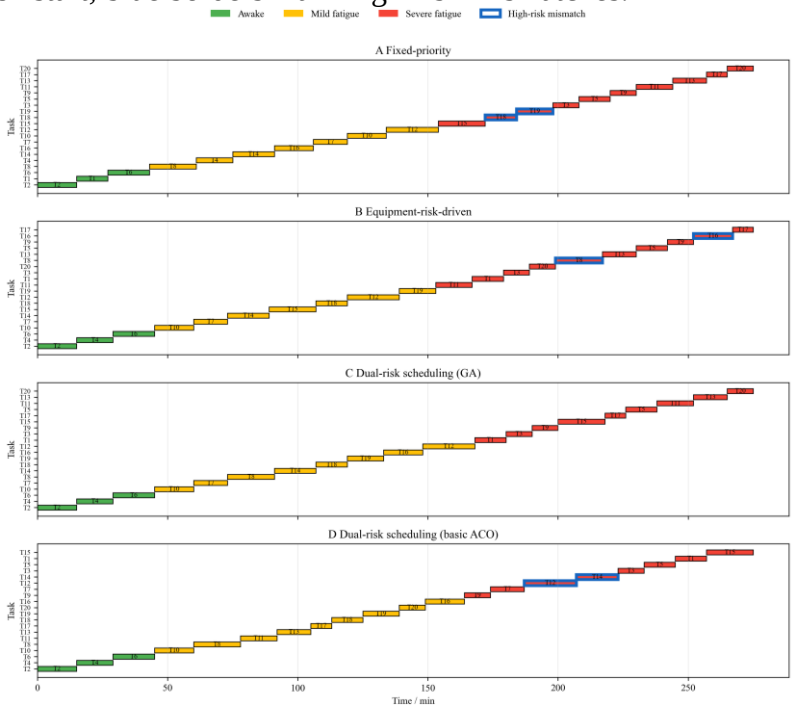


Figure 2: Gantt chart of task execution under different scheduling schemes.

Scheme A sorts tasks merely by priority and does not consider operator fatigue status. As a result, two highly-sensitive tasks, T18 and T19, are scheduled consecutively within the severe-fatigue period of 172-198 min. This indicates that priority-based scheduling may assign high-sensitivity tasks to time intervals when the operator is already fatigued.

Scheme B sorts tasks according to equipment-side risk but still ignores operator fatigue status. Although this strategy prioritizes high-risk equipment, it schedules two highly-sensitive tasks, T8 and

T16, during severe-fatigue periods. This suggests that equipment-risk-driven scheduling cannot guarantee a proper match between task sensitivity and operator status.

Scheme C incorporates fatigue status and the high-risk mismatch penalty. Under the start-time-based criterion, Scheme C has no high-risk mismatches: no highly sensitive task starts when the operator is severely fatigued. Scheme D also adopts the dual-risk model yet still yields two high-risk mismatches, showing that the final schedule is also affected by the search performance of the selected algorithm. To further illustrate how Scheme C adjusts the execution timing of key tasks, Table 3 lists the start-time variations of several highly-sensitive tasks under different schemes.

Table 3: Execution timing adjustment of key highly sensitive tasks.

Baseline scheme	Task	Equipment	S_i	Baseline start/min	SchemeC start/min	Change/min	Fatigue state in SchemeC
A	T18	E2	3	172	107	-65	Mild
A	T19	E4	3	184	119	-65	Mild
B	T8	E8	3	199	73	-126	Mild
B	T16	E8	3	252	133	-119	Mild

As shown in Table 3, Scheme C advances T18 and T19 in Scheme A by 65 min respectively, shifting them from the severe fatigue stage to the mild fatigue stage. Compared with Scheme B, Scheme C advances T8 and T16 by 126 min and 119 min respectively, also shifting the tasks from the severe fatigue stage to the mild fatigue stage. This result indicates that after introducing the operator fatigue state, the scheduling model can actively adjust the execution timing of highly sensitive tasks and move key tasks out of the high-fatigue risk window.

A sensitivity analysis was also conducted. When the safety weight increased from 0 to 0.4, the high-risk mismatch count decreased from 3 to 0. When the safety weight further increased to 1.0, the safety objective decreased to 2.0541, while the delay penalty increased to 3394.0. This indicates a clear trade-off between safety preference and response efficiency.

5. Conclusion

This paper presents a case study on maintenance-decision scheduling that integrates operator fatigue and equipment failure risk for a single-operator central control room of intelligent Baijiu brewing. Operator fatigue is quantified as fatigue-related human-error risk; equipment degradation risk is characterized by the Weibull conditional failure probability; and an equipment-fatigue sensitivity coefficient is introduced to construct a coupled fatigue-equipment risk model. A dual-objective scheduling model is further developed to balance system safety risk and task response efficiency.

The case results show that the GA-based dual-risk scheduling scheme achieves a composite objective value of 0.5560, outperforming the fixed-priority scheme (0.6247) and the equipment-risk-driven scheme (0.6511). The count of high-risk human-machine mismatches decreases from 2 to 0. These results indicate that fatigue status should be regarded not merely as warning information, but also as a scheduling input for highly-sensitive maintenance tasks.

Future research could focus on calibrating the model with operational data from Baijiu enterprises and extending the model to multi-operator and multi-shift scenarios. Furthermore, the proposed framework can be extended to more complex multi-stage manufacturing environments to improve its applicability and scalability for practical industrial applications.

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