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HEURISTICS FOR NOISE-SAFE JOB-ROTATION PROBLEMS CONSIDERING LEARNING-FORGETTING AND BOREDOM-INDUCED JOB DISSATISFACTION EFFECTS

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Abstract

In mitigating occupational hazards, there is often a need to use administrative controls such as job rotation over a prolonged period until the hazards can be eliminated or mitigated to safe levels. This research develops a noise-safe job-rotation optimization model that accounts for learning, forgetting, and boredom effects. Our analysis focuses on the case of human-paced and labor-intensive operations, considering the trade-off between safety and productivity. A case of multi-skilled workers that have heterogeneous skill levels with varying problem sizes is used to demonstrate the model's capabilities. A genetic algorithm and a randomized greedy algorithm are developed and shown to be effective in solving large-scale safe job rotation problems. Our results also show how the boredom and forgetting effects create productivity delays when job rotation is used.

Keywords: heuristics, job rotation scheduling, job satisfaction, learning-forgetting, occupational hazards

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1. Introduction

In assembly lines and manufacturing processes, a significant number of workers repeatedly perform tasks in the same area throughout the workday. These workers have a high chance to be repeatedly exposed to several occupational hazards. This is particularly true in harsh working environments in steel manufacturing, foundry, and other heavy industries. The occupational hazards encountered by workers may vary across different types of workplaces. Noise is a prevalent physical hazard in heavy industry such as construction and manufacturing (Subramaniam et al., 2019). Brief exposure to very intense noise can result in temporary or acute hearing damage. A lower level of noise can still pose a threat if a worker is exposed to it over a prolonged period. Possible consequences are hearing ability impairment (Sliwinska-Kowalska and Davis, 2012) and many other adverse physiological and psychological effects (Al-Dosky et al., 2014). In an industrial workplace, there can be various noise sources including vibration, conveyors, rotating parts, gas leaks, and mechanical press. A mixture of engineering and administrative control techniques is employed as needed, to obtain a desirable safety outcome (Tuli et al., 2020).

According to the National Institute of Occupational Safety and Health (NIOSH) hierarchy of

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noise hazard controls, job rotation is an administrative control method that can be used to reduce the noise exposure of workers to safer levels. When noise cannot be eliminated or reduced to a completely safe level, job-rotation planning can be used as a temporary measure to keep the noise exposure of workers within acceptable limits, until engineering controls can be implemented successfully. In many cases, safe job rotation can be employed as a supplementary means of ensuring worker safety along with engineering controls. The development of safe job-rotation techniques has been documented in the literature of workforce scheduling for health and safety, as described in the literature review section.

One of the primary concerns in safe job-rotation scheduling is to examine the effects of job rotation on important manufacturing variables such as skill learning and forgetting, job satisfaction, and productivity. When workers are transferred to new tasks, they have a chance to learn new skills, leading to manufacturing flexibility improvement.

However, the learning process for any particular set of skills can be disrupted and the trend of improvement in performance may cease to progress. This situation normally applies to the case of skilled or semi-skilled labor tasks. The rotation of workers based on safety criteria may disrupt a worker's learning process and impede their ability to achieve the desired productivity and quality outcomes. The effects of job rotation on workers' job satisfaction is also another issue to be considered in workforce scheduling. Job satisfaction of workers can be defined in many different ways and can be affected by many factors. For example, features such as working time, co-workers, variety in tasks, and work intensity, are important factors affecting job satisfaction in the workforce scheduling context (Katsikea et al., 2011). Work schedule that focuses solely on productivity aspects may adversely affect workers' job satisfaction.

In the safe job-rotation scheduling research domain, there is still a need to investigate the linkage between worker and task characteristics and their effects on productivity and job satisfaction outcomes. The development of safe job-rotation approaches on these aspects is still inadequately explored, as discussed in the next section. This study develops noise-safe job-rotation models that account for the effects of job rotation on skill learning and forgetting and job satisfaction. This study also develops a randomized greedy algorithm and a genetic algorithm to solve the complex non-linear scheduling problem. The solution approaches are tested on instances of different problem sizes, and managerial insights are provided.

The remainder of this paper is organized as follows. Section 2 provides a literature review on the role of job-rotation scheduling in occupational health and safety.

The research methodology, including optimization models, is explained in detail in Section 3. In Section 4, the solution approaches and the details of the computational analysis are presented. Finally, the conclusion is given at the end of the paper.

2. Previous studies and analyses

The development of job-rotation workforce scheduling has focused on problems pertaining to occupational health and safety. Researchers have analyzed occupational hazard and process parameters and have used mathematical-optimization modeling techniques in developing safe job-rotation models (Asensio-Cuesta et al., 2019; Ayough et al., 2020; Diego-Mas, 2020; Digiesi et al., 2018; Moussavi et al., 2018; Moussavi et al., 2019; Otto and Battaïa, 2017; Srinakorn and Olapiriyakul, 2020). Generally, the modeling objectives are to reduce occupational hazard exposure and to create safer working conditions for workers.

In the context of noise hazards, a homogeneous workforce with identical workers is usually considered in the early development of job-rotation models. The administrative controls frequently studied include limiting the number of workers exposed to hazardous noise (Nanthavanij and Yenradee, 1999) and the maximum daily noise exposure level of workers (Tharmmaphornphilas et al., 2003). A number of papers incorporate the noise issue within job-rotation models. For instance, Asawarungsaengkul and Nanthavanij (2006) develop noise-safe job-rotation models and examine the effects of budget constraints on the model implementation. Different control objectives are formulated in their model, including the minimization of rotation frequency, workforce size, and protective equipment usage. Other noise-safe job-rotation models focus on evaluating the effects of process discontinuities caused by the rotation of workers and their subsequent impacts, in terms of productivity loss. The modeling objectives can be formulated to minimize the number of rotations needed for keeping workers safe (Asawarungsaengkul and Nanthavanij, 2008) or to minimize the productivity loss caused by unnecessary rotation (Rerkjirattikarn et al., 2017).

In practice, under a job-rotation plan, manufacturing workers tend to rotate between tasks with different skill requirements and responsibilities. According to the recent review by Padula et al. (2017), many proposed noise-exposure control strategies consider a heterogeneous workforce where there exist between-worker differences in skill and occupational exposure risk. For noise, all workers are subject to the same daily permissible limit. For ergonomic hazards, the job-rotation design has to consider the worker heterogeneity in personal tolerance to occupational risks (Boenzi et al., 2016; Mossa et al., 2016). When considering skill-related subjects simultaneously, the formulation and solving of noise-safe job-rotation models generally require complex mathematical modeling and problem-solving techniques. There are several aspects of skill consideration. Job-rotation optimization can be constrained by the skill limitations of individual workers, as shown by previous studies (Rattanamanee and Nanthavanij, 2013; Hochdörffer et al., 2018). As shown in previous noise-safe skill-based job-rotation studies, worker skill attributes need to be defined, enabling the classification of workers based on their ability to perform a set of tasks (Deljoo et al., 2009; Rerkjirattikarn et al., 2018). The issues of a worker's skill development have also been investigated by previous research. When skill development is included as one of the primary scheduling goals, the assignment of workers to jobs over a sufficiently-long scheduling horizon also needs to be performed. Consequently, the formulation and solving of skill-based job-rotation models generally require complex mathematical modeling and problem-solving techniques.

Heuristic and metaheuristic approaches have been used in solving safe job-rotation problems more frequently over the past decade. Asawarungsaengkul and Nanthavanij (2008) show that a genetic algorithm (GA), with a customized initial population search, can be used as an effective alternative solving approach for the optimization of a standard noise-safe job-rotation problem. This is one of the few heuristic-based studies that focused on the mitigation of noise exposure among workers. A GA is used in several safe job-rotation research papers to deal with different assignment parameters, scheduling criteria, and worker characteristics. For instance, Diego-Mas et al. (2009) developed GA-based software that can compare job requirements with worker abilities. The parameters related to workers' capacities, preferences, and physical limitations, including the temporary or permanent disabilities of workers for certain tasks, are considered. The problem complexity of noise-safe job-rotation problems can be more difficult to manage using only deterministic optimization tools when engaging in multi-objective formulations. The work by Nanthavanij et al. (2010) may be the first skill-based job-rotation study that allows both the safety and productivity objectives to be simultaneously achieved. Their study uses a heuristic method to solve a worker-task-period assignment problem, considering safety and worker competency. After 2010, the use of GA and heuristic solving approaches for multi-objective ergonomic job-rotation problems has appeared in the literature (Asensio-Cuesta et al., 2012; Sana et al., 2019; Wongwien and Nanthavanij, 2017a).

Job satisfaction is another important workforce management aspect that has yet to receive sufficient research attention, particularly for safe job rotation in the manufacturing industry. Preference-based job-rotation scheduling models have been developed for achieving a higher degree of workforce job satisfaction. Such job-rotation scheduling requires that the heterogeneous preferences of workers in the working environment are evaluated. Wongwien and Nanthavanij (2017b) develop a multi-objective safe job-rotation optimization approach, where one of the objectives is to maximize the workers' job satisfaction, based on their preferences for specific jobs and coworkers. In their model, worker satisfaction is maximized while ensuring that the performance related to productivity and ergonomic safety meets the specified requirements. Asensio-Cuesta et al. (2019) develop and apply a job-rotation scheduling model based on game theory to a case where the preference and competence for each job position of each worker are considered. Their proposed model helps balance the level of exposure and the repetitiveness of workers. The noise-safe job-rotation study by Rerkjirattikal and Olapiriyakul (2019) focuses on worker satisfaction that is relevant to the preferred overtime hours. Many job satisfaction factors can be considered for safe job rotation in the manufacturing industry. For example, for jobs with extended working hours and irregular shifts, job satisfaction can be related to work time preferences and the fairness in scheduling, as shown by the scheduling studies in the service sector (Lin et al., 2015; Maenhout and Vanhoucke, 2010; Stolletz, 2010). Fairness in scheduling can be achieved by considering both the employer and employee objectives, which regularly conflict with each other in workforce scheduling (Shahnazari-Shahrezaei et al., 2013).

Based on the aforementioned literature, safe job-rotation scheduling research is relevant to scheduling issues where there exist the effects of job rotation on psychological variables, human behavior, and human cognitive performance. Skills and job satisfaction need to be considered simultaneously along with the safety of workers, especially when job rotation is to be used to mitigate hazard exposure on a regular basis or for a prolonged period. However, the consideration of these aspects (together with safety issues) is still limited in the literature. To strengthen this research domain, this study develops a noise-safe job-rotation scheduling model that considers the effects of job rotation on skill development, job satisfaction, and their interrelated effects on productivity.

The learning and forgetting mechanisms and job satisfaction concepts addressed by Azizi et al. (2010) are employed in our study in the context of noise-safe job rotation. The case of independent parallel workstations is considered in this study. Such a case is used by Wang and Wang (2014) to demonstrate the effects of skill learning and skill deterioration in a workforce scheduling problem. We also consider the heterogeneous patterns of learning and forgetting rates among workers, which are important workforce characteristics for the investigation of assembly line productivity (Shafer et al., 2001). Our model also incorporates the job-rotation effects, to reduce boredom-induced job dissatisfaction, which is a factor that deteriorates worker productivity.

Another contribution of this research is to develop ad-hoc heuristic algorithms or meta-heuristic algorithms to solve the problems, efficiently and accurately. There is still a need for effective problem-solving algorithms that can handle practical-size job-rotation workforce scheduling problems with a large number of workers, tasks, and workdays. Such job-rotation scheduling problems are NP-hard even for small to moderately sized worker-task assignments (Coffman et al., 1996; Otto and Scholl, 2012).

3. Methodology

In this section, we describe the methodologies used to consider the three key issues in our safe job-rotation scheduling, namely, noise exposure, skill learning and forgetting, and job satisfaction. These issues are then incorporated into a non-linear optimization model. To help understand the use of this model, the fundamental assumptions concerning the application of the model are clarified here.

Assumptions

- A group of workers indexed by i = {1,…, I} are assigned to tasks indexed by j = {1,…, J} over a number of 4-hour shifts indexed by t ={1,…, T}.
- Workers can be rotated to perform tasks at different workstations, at the end of the first 4-hour shift. There are two 4-hour shifts in a workday.
- The daily permissible noise exposure limit is 85 dBA according to NIOSH recommended exposure limit (NIOSH, 1998).
- During each shift, every workstation requires one worker to perform the task and each worker can perform the task at only one workstation.
- The frequency of shift rotation has an impact on both job satisfaction and skill learning and forgetting, which are factors that affect productivity.

3.1. Noise exposure assessment

Noise measuring instruments are normally deployed in the field to monitor noise levels at a workplace. Noise mapping can be performed to provide management with a visual representation of the sound level distribution at a workplace. For managing and controlling noise exposure, the noise exposure intensity and the amount of exposure time of workers can be calculated in the unit of daily noise dose (DND). When a workday consists of two or more working shifts, the DND can be calculated using Eqs. (1-2) (NIOSH, 1998). For a noise-safe schedule, the DND of all workers must be lower than or equal to 1.0.

$$DND = \sum_{i=1}^{I} \frac{C_i}{TAE_i} \tag{1}$$

$$TAE_i = \frac{8}{2^{\frac{L-85}{5}}} \tag{2}$$

where: C_i - exposure duration, at each noise level L; L - level of noise exposure, measured at each workstation; TAE_i - allowable exposure duration, corresponding to the noise exposure level.

3.2. Skill learning and forgetting

When a worker performs the same task repetitively in sequence, the learning effect phenomenon occurs, resulting in a decrease in task processing time. When there is a gap or idle time between consecutive operations, the forgetting effect occurs, causing the task processing time to be longer than normal. Fundamental learning and forgetting mechanisms are the basis of various learning and forgetting models. These models have a range of definitions that vary according to the nature of tasks, work pace, individual preexisting experience, and many other worker-process characteristics (Li et al., 2018). This study employs the learning and forgetting mechanisms previously addressed in a previous workforce scheduling study by Azizi et al. (2010). Their scheduling model incorporates important characteristics of human-paced operations that affect the learning and forgetting rates.

These characteristics are the individual differences in skill learning and forgetting, steady-state (maximum) and lower-bound performance levels, and the exponential pattern of changes in skill improvement and deterioration. The exponential pattern is suitable for our case due to the ability to incorporate worker's prior experience, which is one of the important worker characteristics to be considered when implementing job rotation. The exponential pattern and its variant forms, including log-linear and hyperbolic patterns, were previously used to create various learning and forgetting models for both manual and cognitive tasks, as reviewed by Nembhard and Uzumeri (2000). These patterns provide a reasonable representation of the rates of growth and decline in worker performance during the learning and forgetting phases. The use of multivariate learning models can also be considered, when there are more than one significant factors affecting the learning process.

The relations among the skill level of workers and the learning and forgetting rates employed in our safe job-rotation scheduling are shown in Eqs. (3-4). The learning phenomenon is a function of the initial/remaining skill level and the task engagement duration. The forgetting phenomenon is a function of departure (away-from-task) duration and the level of skill gained before the interruption.

$$S_{i,j,t} = S_{\max} - \left(S_{\max} - S_{rem,i,j,t}\right) \times e^{\beta_i \cdot D_{w,i,j,t}} \tag{3}$$

$$S_{rem,i,j,t} = S_{bd,i,j} \times e^{\gamma_i \cdot D_{d,i,j,t}} \tag{4}$$

where: $S_{i,j,t}$ is the skill level of worker i for task j on period t; $S_{\max}$ is the maximum skill threshold level for all tasks and for all workers; $S_{rem,i,j,t}$ is the remnant skill of worker i for task j in period t; $S_{bd,i,j}$ is the skill level of worker i when departing task j; β_i is the learning slope of worker i; γ_i is the forgetting slope of worker i; $D_{w,i,j,t}$ is the working duration for worker i on task j in period t; $D_{d,i,j,t}$ is the departure duration for worker i on task j in period t.

In this study, the skill level of workers is related to the standard production time required by workers to perform tasks and produce a unit of output. S_{max} is defined as the skill level required to reach the standard production time of tasks. $S_{bd,i,j}$ is defined as the skill level of worker *i* before departing task *j*. Alternatively, the skill level of workers can be related to the productivity of workers in a working period, as in a study by Pérez-Wheelock and Huynh (2018). The learning and forgetting behaviors of workers have a direct influence on their skill-proficiency development. A higher learning rate combined with a longer task engagement duration results in a more effective learning outcome.

However, when workers are assigned to different tasks, their skill proficiency that was required to perform the previous tasks starts to deteriorate due to the forgetting effect. In our problem settings, workers' skill proficiency varies according to individual skill learning and forgetting rates, but stays within the same initial (minimum) and maximum skill-proficiency limits. While excessive rotation of workers can adversely affect the productivity outcomes, inadequate rotation frequency may hinder the ability of the scheduling plan to mitigate boredom-induced job dissatisfaction and noise exposure among workers.

3.3. Job satisfaction

Job satisfaction is an individual's general attitude, usually referred to as the level of positive emotional state, toward his or her job. A variety of factors affect the job satisfaction of workers, including career achievement at the workplace, knowledge learning opportunity (Varshney, 2019), work-life support (Chen et al., 2019), and workplace safety perception (Joshi, 2019). Job boredom can be defined as the unpleasant and dissatisfying emotional state of workers caused by an inadequately stimulating work environment. In this study, we deal with the case of a highly repetitive manufacturing process where the job boredom and job preferences of workers act as the main contributors to their job satisfaction and productivity performance. We define job preferences as a worker's attitudes toward tasks. Workers can regard tasks as preferred and non-preferred tasks. Job boredom is the psychological strain occurring when workers repetitively perform tasks. While performing tasks, the job satisfaction of workers declines according to the individual boredom slope over the task engagement duration, according to the relationship depicted in Eqs. (5-6).

$$V_{i,t} = V_{\max} - \left(V_{\max} - V_{i,t-1}\right) \times e^{\tau_i \cdot \left(\sum_{j=1}^{J} D_{w,i,j,t} + UD_{i,t}\right)} \tag{5}$$

$$UD_{i,t} = \left(\sum_{j=1}^{J} D_{w,i,j,t-1}\right)\left(1 - \sum_{j=1}^{J}\left(X_{i,j,t-1} \cdot X_{i,j,t}\right)\right) + \left(UD_{i,t-1} \cdot \sum_{j=1}^{J}\left(Y_{i,j,t} \cdot X_{i,j,t}\right)\right) \tag{6}$$

where: $V_{i,t}$ is the satisfaction level of worker *i* in period *t*; V_{max} is the maximum satisfaction level; $V_{i,j,t-1}$ is the satisfaction level of worker *i* for task *j*, one period prior to period *t*; τ_i is the boredom slope of worker *i*; UD_{it} is the non-restoration variable occurs along with undesirable assignments, causing unrestored satisfaction level; $D_{w,i,j,t}$ is the working duration for worker *i* on task *j* in period *t;* $X_{i,j,t}$ is the binary task assignment variables, equal to 1 when worker *i* is assigned to perform task *j* in period *t*, 0 otherwise; $Y_{i,j,t}$ is the binary task preferable variables, equal to 1 when worker *i* is assigned to perform non-preferred task *j* during period *t*, 0 otherwise.

When workers are rotated to perform new tasks, job satisfaction can be restored. At this point, the restoration of job satisfaction can occur, depending on how worker-task characteristics are considered. In our study, we restrict our attention to job preferences which are frequently cited characteristics in the workforce scheduling literature (Pawar and Hanchate, 2013). It is rational to assume that the restoration of the workers' job satisfaction is triggered only if they are rotated to their preferred tasks. When workers are assigned to their non-preferred tasks, the non-restoration variables (UD), shown in Eqs. (5-6), keep their satisfaction levels from being restored. This restoration mechanism can be modified based on other worker-task characteristics, to realize alternative model implementation approaches. For instance, the effects of task similarity on job boredom have been considered (Ayough et al., 2012). In this study, the maximum and minimum threshold satisfaction levels of workers are defined. It is assumed that the variation of worker satisfaction levels within these thresholds over the job-rotation period has a direct effect on productivity. Workers with higher job satisfaction can perform tasks with higher productivity. However, when workers are not equipped with sufficient levels of skill proficiency and job satisfaction, their productivity rate will be lower than the standard rate. This leads to a delay in achieving production targets. In the following sections, such a productivity shortcoming is called a delay and expressed in terms of the additional amount of time in minutes that is required to reach production targets. In practice, boredom-induced job dissatisfaction effects can be estimated by assessing the deviation from standard production time or the number of units they can produce in a given time limit. Between satisfactory and unsatisfactory working conditions, the productivity of workers under unsatisfactory conditions is significantly lower (Shikdar and Das, 2003).

3.4. Non-linear optimization modeling

The safe job-rotation problem in this study is solved using an optimization model, which comprises the following components.

Decision variables

$X_{i,j,t}$ binary task assignment variables, equal to 1 when worker *i* is assigned to perform task *j* in period *t*, 0 otherwise

$S_{i,j,t}$ skill level of worker *i* for task *j* in period *t*
$S_{rem,i,j,t}$ skill remnant of worker *i* for task *j* in period *t*
$S_{bd,i,j}$ skill before departure of worker *i* in task *j*
$V_{i,t}$ satisfaction level of worker *i* in period *t*
$D_{w,i,j,t}$ working duration for worker *i* on task *j* in period *t*
$D_{d,i,j,t}$ departure duration for worker *i* on task *j* in period *t*

Parameters
$S_{\max}$ maximum skill level
$V_{\max}$ maximum satisfaction level
H number of workhours per period
$Dose_J$ noise dose generated by task *j*
α weight of importance factor
β_i learning slope of worker *i*
γ_i forgetting slope of worker *i*
τ_i boredom slope of worker *i*
T_j maximum delay of machine *j*
$Y_{i,j,t}$ binary task preference variables, equal to 1 when worker *i* is assigned to perform a non-preferred task *j* during period *t*, 0 otherwise.

The non-linear objective function (Eq. 7) minimizes the total delay caused by the deficiency of skill and job satisfaction. The parameter *α* is the weighting factor that indicates the amount of influence each deficiency has on the delay. (Eq. 8) limits the daily noise dose of workers to be less than 1.0. (Eq. 9) ensures that a worker can perform only one task at a time. (Eq. 10) keeps track of working durations when workers perform task *j* continuously. The working duration is set to zero when a worker is rotated to perform the task at a new workstation. (Eq. 11) keeps track of the departure duration of worker *i* from task *j* until the worker is reassigned to task *j*. (Eq. 12) calculates the skill level of worker *i* for task *j* during period *t*. (Eq. 13) computes the skill level of worker *i*, gained before being rotated from task *j*. (Eq. 14) calculates a worker *i* remnant skill for task *j* after being reassigned to the task. (Eq. 15) computes the satisfaction levels of workers in each period *t*. (Eq. 16) keeps the job satisfaction of worker *i* from being restored when assigned to non-preferred tasks in period *t*. The proposed job-rotation model is developed to determine a safe job-rotation schedule for a large group of workers over a long planning horizon. A number of parameters are involved, including the noise exposure levels, skill learning and forgetting rates, and job satisfaction levels. The use of exact approaches may not be practical for large problem sizes, especially when the rotation schedule is required in a short period. Experimentation with varying problem sizes is performed in this study to address this practical issue for the exact and different heuristic-based solving approaches. The sensitivity analysis results are shown in the results and discussion section.

The objective function of the model can be expressed as (Eq. 7):

$$Minimize \sum_{i=1} \sum_{j=1} \sum_{t=1} \left[\left(\frac{S_{\max} - S_{i,j,t}}{S_{\max}} \right) \alpha + \left(\frac{V_{\max} - V_{i,t}}{V_{\max}} \right) (1-\alpha) \right] \cdot \mathrm{T}_j \cdot X_{i,j,t} \tag{7}$$

Subject to Eqs. (8-16):

$$\sum_{i=1}^{I} \sum_{t=1}^{T} X_{i,j,t} \cdot Dose_j \leq 1 \tag{8}$$

$$\sum_{j=1}^{J} X_{i,j,t} \leq 1 \tag{9}$$

$$D_{w.i.j.t} = \left[\left(D_{w,i,j,t} + X_{i,j,t} \right) \cdot X_{i,j,t} \right] \cdot H \tag{10}$$

$$D_{d,i,j,t} = \left[\left(D_{d,i,j,t} + 1 \right) \left(1 - X_{i,j,t} \right) \right] \cdot H \tag{11}$$

$$S_{i,j,t} = S_{\max} - \left(S_{\max} - S_{rem,i,j,t} \right) \times e^{\beta_i \cdot D_{w,i,j,t}} \tag{12}$$

$$S_{bd,i,j,t} = \left[S_{bd,i,j,t-1} \left(1 - X_{i,j,t} \right) \right] + \left[S_{i,j,t-1} \left(1 - X_{i,j,t} \right) \right] \tag{13}$$

$$S_{rem,i,j,t} = S_{bd,i,j} e^{\gamma_i \cdot D_{d,i,j,t}} \tag{14}$$

$$V_{i,t} = V_{\max} - \left(V_{\max} - V_{i,t-1} \right) \times e^{\tau_i \cdot \left(\sum_{j=1}^{J} D_{w,i,j,t} + UD_{i,t} \right)} \tag{15}$$

$$UD_{i,t} = \left(\sum_{j=1}^{J} D_{w,i,j,t-1} \right) \left(1 - \sum_{j=1}^{J} \left(X_{i,j,t-1} \cdot X_{i,j,t} \right) \right) + \left(UD_{i,t-1} \cdot \sum_{j=1}^{J} \left(Y_{i,j,t} \cdot X_{i,j,t} \right) \right) \tag{16}$$

3.5. Enumerative algorithm (EA)

The enumerative algorithm is implemented to observe all possible solutions by trying out all possible combinations of worker-task assignments. Then, it selects the solution with the best objective value.

3.6. Initialization algorithm

We present in this section an algorithm that generates the initial noise-safe job-rotation schedules, considering the learning-forgetting and satisfaction effects on system productivity. This initialization algorithm is incorporated into the randomized greedy algorithm (RGA) and genetic algorithm (GA), used to solve the noise-safe job-rotation problem. At the first iteration, the algorithm randomly assigns workers to tasks without considering worker skill or satisfaction. From the second iteration onwards, workers are sorted based on the accumulated DND in descending order. Then the algorithm assigns the task that yields the lowest delay to the worker with the highest DND, without violating the noise restriction. A flowchart of the initialization algorithm is shown in Fig. 1.

3.7. Randomized Greedy Algorithm (RGA)

The RGA is an approach that iterates the initialization algorithm depicted in Section 3.6, for a certain number of iterations.

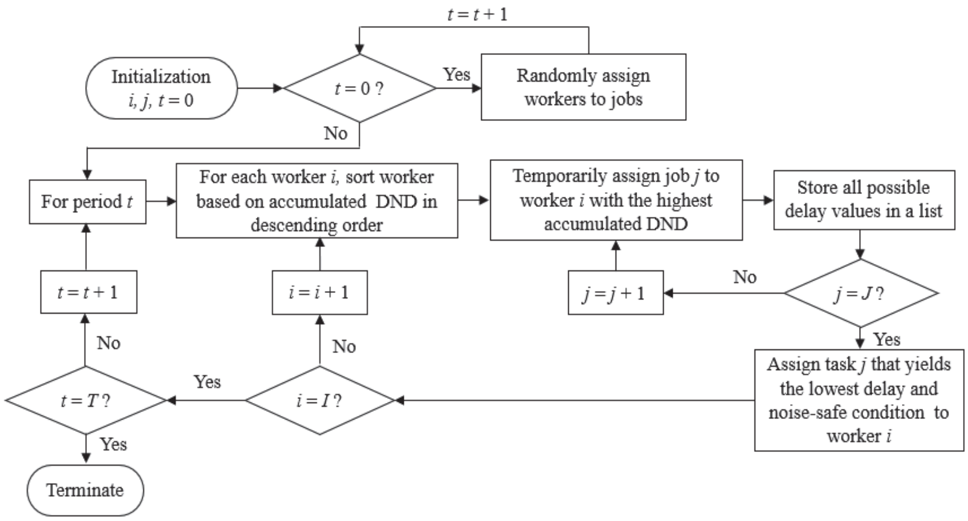


Fig. 1. Flowchart of the initialization algorithm

Then, it selects the solution with the best objective value. The RGA can be decomposed into the following steps.

Step 1: For each iteration n until N iterations, implement the initialization algorithm and record the result.

Step 2: If n equals to N, the collected results are compared and the optimum value is selected.

3.8. Genetic Algorithm (GA)

The fitness value of the GA is defined as the reciprocal of the total delay because we want to minimize the adverse productivity effects of a lack of skill and boredom. Solutions with less delay have a higher probability of being selected. Our GA algorithm can be described according to the following steps.

Step 1: Generate a random initial population using the initialization algorithm, mentioned in Section 3.6.

Step 2: Evaluate the fitness value (FV) of each chromosome (Eq. 17):

$$FV = \frac{1}{Total\ delay} \tag{17}$$

Step 3: Select the parents from the initial population using the roulette selection method.

Step 4: Crossover the selected parents at some crossover rates to generate offspring.

Step 5: Perform a feasibility check for any unassigned tasks or over-limit DND. If not feasible, reassign tasks until the chromosome is feasible.

Step 6: At a certain mutation rate, genes in chromosomes are altered and rechecked for any infeasibility. If not feasible, reassign tasks until the chromosome is feasible.

Step 7: Combine parents and offspring population. Then, repeat step 2 until the termination condition is met.

3.9. Simulated Annealing (SA)

SA is a metaheuristics algorithm, well-known for its ability to escape local extrema by using perturbation to improve the initial solution. The algorithm also allows perturbation that worsens the solutions to ensure the escape from local extrema (Gallo and Capozzi, 2019). In our study, SA was applied after the GA as a means to assess and improve the best solution found. The proposed SA is implemented according to the following steps.

Step 1: Set the initial solution as the current solution, from m until M and n until N.

Step 2: Randomly generate a new solution

Step 3: Identify if the new solution is better than the current one. If so, go to Step 3.1, else go to Step 3.2.

Step 3.1: Set the new solution as the current solution. Then update the value of n to n+1.

Step 3.2: Compute the probability of accepting bad solutions and generate a random number. If the random number is lesser than the probability, set the new solution as the current solution, then update the value of n to n+1. If the random number is higher than the probability, the current solution remains the same and update the value of n to n+1.

Step 4: If n = N, update the value of m to m+1 and T = alpha*T.

Step 5: If m = M, look for the solution that has the best objective function.

4. Results and discussion

Our analysis validates the proposed model and solving approaches and demonstrates the impact of different job rotation plans on productivity delay. To demonstrate the use of the proposed model, we firstly investigate the effects of α and select the most appropriate α value. This α value is used in the remaining analyses, where the computational efficiency of four different solving approaches, GA, RGA, NLP, and EA, is evaluated. Finally, we compare one of the job-rotation cases to a non-rotation plan to gain an insight into the amount of delay incurred by the skill and satisfaction factors and the need to rotate workers based on the noise exposure limit.

4.1. Numerical example

A numerical example representing a manufacturing process consisting of heterogeneous tasks requiring different skills is used. The number of workers available for the job-rotation schedule is equal to the number of tasks. The learning, forgetting, and boredom slopes of workers are taken directly from Azizi et al. (2010), as given in Table 1. The workers' non-preferred tasks are also listed in the table. During the job-rotation planning period of 5 days, workers are rotated among workstations and exposed to different noise levels, as indicated in Table 2. In the same table, the levels of exposure are calculated, based on the noise levels and exposure duration of 4 hours. The maximum delay for each workstation is also provided.

Table 1. Learning, forgetting, and boredom slopes of workers

Worker	***Learning Slope (β)***	***Forgetting Slope (γ)***	***Boredom Slope (τ)***	***Non-preferred tasks***
1	-0.20	-0.12	0.15	3
2	-0.23	-0.15	0.17	5
3	-0.19	-0.20	0.14	4
4	-0.30	-0.25	0.21	5
5	-0.21	-0.08	0.17	1.3
6	-0.22	-0.13	0.13	9
7	-0.18	-0.10	0.11	9
8	-0.25	-0.15	0.21	5
9	-0.18	-0.21	0.11	-
10	-0.17	-0.27	0.12	3

4.2. Effects of α

In our study, the weight of importance, denoted as α, is assigned to the objective equation. The weight coefficient allows decision-makers to assign appropriate priority levels to skill development and job satisfaction issues. Based on (Eq. 7), the goal of minimizing the total delay while keeping the daily noise dose among workers within the permissible limit can be greatly affected by α. The larger the value of α, the higher priority is given to workers' skill proficiency than to workers' job satisfaction. We examine the effects of α by varying its value to be 0.25, 0.5, and to 0.75, and selecting the most appropriate α value based on the amount of delay. The proposed model is solved, for the case of 5 workers and 5 workstations over the period of 5 workdays, to determine the delay and the number of non-preferred task assignments that occurred.

The results are shown in Table 3. According to the results, an α of 0.75 results in much less delay compared to that of other α values and is selected to be used in the remaining analysis. In the case where the delay differences among α values are less significant, smaller α values can be used to promote a motivating work environment for workers.

Table 2. Noise levels, noise dose, and standard production time at each workstation

Workstation	***Noise levels (dBA)***	***Noise Dose (D_j)***	***Maximum delay (T_j)***
1	62.9	0.02	30
2	93.7	1.66	30
3	93.7	1.66	29
4	91.5	1.23	15
5	91.5	1.23	20
6	88.5	0.81	30
7	88.5	0.81	27
8	92.5	1.42	39
9	92.5	1.42	29
10	85.1	0.51	30

Table 3. Effects of α on the delay and the number of non-preferred task assignments

α	***0.25***	***0.5***	***0.75***
Total delay (minutes)	543.78	493.74	402.03
No. of non-preferred task assignments	0	5	5

4.3. Comparison of solving approaches

The problem is solved using EA, NLP, GA, and RGA. The computation efficiency of these solving approaches is investigated for different problem sizes. We vary the number of workers and tasks from 5 to 60, as shown in Table 4. In the table, the total delay in minutes and the solving time in seconds are given. For EA, the problem is solvable only for the case of assigning 5 workers to 5 tasks over a 1-day (2 periods) operation, denoted as 5w-5t (2p). For other cases, where the job-rotation scheduling period is 5 days, NLP enables us to obtain the solutions for cases of up to 9 workers and 9 tasks. The GA and RGA can be used for all problem sizes where the number of workers and the number of tasks reach 60. The total delay is the accumulated amount of delay across the scheduling period of 5 8-hour workdays.

It is shown that the use of the GA enables us to reach solutions with the least amount of delay. The RGA provides a slightly higher delay, but the computational time is much less. In the right-most columns, we compare the results obtained via the RGA, NLP, and EA with those obtained by the GA. The comparison shows that NLP is not as efficient as the other methods. The use of the RGA is more practical for problems requiring quick management responses, especially for large problem sizes. Finally, SA is used to verify that the GA results are not local extrema. For each problem size, the best solution found by the GA is further analysed by SA to see if the solution can be improved. In Table 4, the empirical results suggest that the solutions found by the GA cannot be improved by the SA.

4.4. Impacts of noise-safe job rotation

This section illustrates the impacts of using the proposed job-rotation scheduling approach to reduce noise exposure. We also disregard the noise issue and solve the numerical example problem again using GA. The results of the scenarios with and without noise exposure control are shown in Fig. 2. Without noise exposure control, workers are assigned to perform tasks at the same workstations throughout a 5-day period solely based on the skill development objective. In this case, some workers are exposed to noise, extremely higher than the daily permissible limit. Regarding job satisfaction, workers' job satisfaction gradually declines due to the boredom effect. When the noise exposure control is implemented, some workers are regularly rotated between tasks for their noise-exposure safety.

In this numerical case, the rotation can reduce the average DND of workers to the safe limit (below 1.0). In the actual work environment with higher noise levels in all workstations, the feasible solution may not be obtained at first due to the noise-dose constraint. The noise-dose constraint may need to be relaxed. The feasible solutions obtained from the relaxed model help to identify and prioritize the workstations that require additional engineering noise control. After reducing the noise, noise exposure assessment and job-rotation optimization can be performed again.

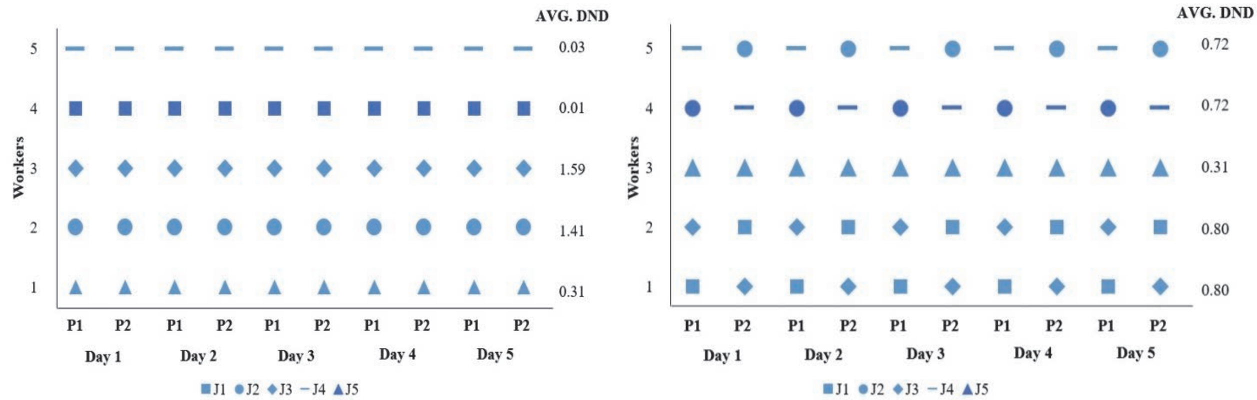
For multi-skill development and job boredom relief opportunities provided by job rotation, a higher priority is given to skill development than to job boredom in the presented case. Workers assigned to workstations with a noise level lower than the permissible limit will not be rotated to minimize the delay due to skill forgetting, which is the case for the worker at J5.

The productivity enhancement due to skill development is achieved at the cost of increased boredom stress of the worker. In a work environment with sufficient production capacity, α can be reduced to improve workers' job satisfaction. By using the proposed model, workers can be constantly rotated to reduce the boredom effects. Despite the positive effects of job rotation, the delay under the noise-safe job-rotation plan (402.03 minutes) is considerably higher than that of the non-rotation plan (341.55 minutes), as shown in Table 5. In the Table, the total delay can be divided into job-satisfaction delay and skill-development delay.

Table 4. Comparison of solving approaches

Problem sizes (worker-task)	*Total delay (minutes)*				*Solving time (seconds)*				*Excessive delay compared to GA solution (%)*			
	EA	*NLP*	*GA*	*RGA*	*EA*	*NLP*	*GA*	*RGA*	*EA*	*NLP*	*RGA*	*GA-SA*
5w-5t (2p)	102.5	106.6	102.5	104.1	190.5	4	58.4	0.0	0%	4%	1.5%	0%
5w-5t	-	581.6	402.0	406.0	-	48	105.1	0.1	-	45%	1.0%	0%
6w-6t	-	651.0	506.4	517.4	-	199.8	984.2	0.3	-	29%	2.2%	0%
7w-7t	-	810.8	568.6	578.1	-	400.2	1836.3	0.6	-	43%	1.7%	0%
8w-8t	-	1018.7	673.8	690.6	-	1021.8	1292.6	0.6	-	51%	2.5%	0%
9w-9t	-	1106.1	802.6	821.4	-	1575	4686.0	0.8	-	38%	2.4%	0%
10w-10t	-	-	890.7	907.6	-	-	2439.9	1.0	-	-	1.9%	0%
20w-20t	-	-	1801.4	1834.4	-	-	3658.9	2.3	-	-	1.8%	0%
30w-30t	-	-	2714.1	2762.4	-	-	3606.0	4.2	-	-	1.8%	0%
40w-40t	-	-	3606.5	3692.2	-	-	3605.8	6.8	-	-	2.4%	0%
50w-50t	-	-	4521.9	4616.4	-	-	3608.1	9.7	-	-	2.1%	0%
60w-60t	-	-	5448.2	5561.9	-	-	3621.7	13.2	-	-	2.1%	0%

EA- Enumerative algorithm, NLP - Non-linear programming, GA - Genetic algorithm, RGA - Randomized greedy algorithm, SA - Simulated annealing algorithm



(a) (b)

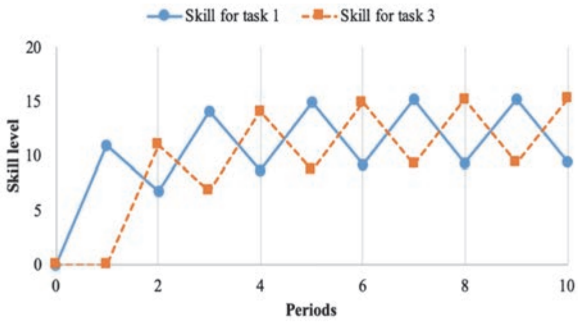
Fig. 2. Comparison between scenarios with and without noise exposure control:
(a) Schedule without noise exposure control; (b) Schedule with noise exposure control

Skill-development delay is caused by 1) the gap between workers' initial skill levels and the skill levels required for standard productivity rates and 2) forgetting effect. The delays due to the forgetting effect are noted in the parentheses.

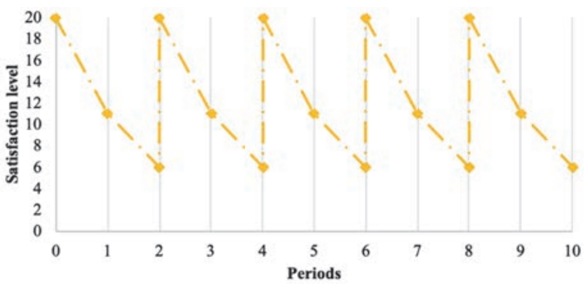
Table 5. Productivity delays of noise-safe job-rotation and non-rotation schedules

Scheduling plan	*Total delay (minutes)*	*Delay due to job satisfaction (minutes)*	*Delay due to skill development (forgetting effect) (minutes)*
Noise-safe job rotation	402.03	136.92	265.11 (186.41)
Non-rotation	341.55	215.23	126.32 (64.41)

The results show that both learning and forgetting effects and boredom effects can contribute significantly to the productivity delay. The effects of job rotation and learning and forgetting rates on worker's skill development and job satisfaction are illustrated in Fig. 3. The changes in the proficiency level of skills for worker 1 are shown in the figure. When the worker moves from task 1 to task 3, the skill-proficiency level for task 1 decreases due to the forgetting effect. At the same time, the skill-proficiency level for task 3 increases due to the learning effect. When moving to task 3, the worker's job satisfaction is not restored because task 3 is worker 1's non-preferred task. The satisfaction keeps decreasing until the worker moves back to task 1.



(a)



(b)

Fig. 3. Impact of job rotation on skill proficiency and job satisfaction for worker 1:(a) Skill proficiency; (b) Satisfaction level

In our numerical case, workers are rotated between two workstations to avoid the skill-forgetting delay, such as the case of worker 1. In other cases, workers may be assigned to rotate among other workstations depending on a worker's learning and forgetting rates. The rotation among other workstations promotes multi-skill development among workers, leading to improved flexibility in workforce management and workers' career opportunities. In an industrial environment, workers can be exposed to multiple occupational hazards. The rotation can reduce the risk of excessive exposure to any hazard other than noise (which is the focus of this study).

5. Conclusions

In mitigating occupational hazards, there is often a need to use administrative controls such as job rotation over a prolonged period until the hazards can be eliminated or mitigated to safe levels. During the job-rotation implementation period, the impacts of job rotation on workers' job satisfaction and skill proficiency development can be significant. However, the two aspects have not been sufficiently investigated in the existing literature. This research contributes to the field by considering the relationship of tasks to workers' skill proficiency and job satisfaction. Skill learning, skill forgetting, and boredom-related job satisfaction are integrated into a noise-safe job-rotation optimization model. This research also contributes to the safe job-rotation scheduling field by demonstrating the use of metaheuristic problem-solving techniques.

The model is formulated using NLP with the objectives of keeping workers safe from excessive noise exposure while minimizing the amount of delay caused by the inability to attain the continuous development of skill proficiency and boredom-induced job dissatisfaction. Since NLP may not be viable due to its NP-hard nature and many non-linear instances in the model, heuristics and metaheuristics algorithms are proposed as alternative solving techniques. An initialization heuristics algorithm coupled with metaheuristics (GA and RGA) is developed and applied to the numerical examples, with a different number of workers and tasks. Different from other research, the proposed algorithm incorporates the effects of noise-safe job-rotation scheduling with skill learning-forgetting and job satisfaction, to improve productivity. The relative performance of the GA and RGA are compared against the EA and NLP, in terms of both optimality and computational burden. Finally, the GA-SA algorithm was applied to improve the GA results, considering SA's ability to escape local extrema.

According to the results, NLP is only viable for small-scale problems, and hence, may not be efficient for a practical problem. The RGA is an efficient solving approach, due to its ability to achieve comparable solutions within a reasonable computational time. The GA can reach very good solutions for all problem sizes but consumes a substantial amount of time. Therefore, the GA may not be appropriate for assigning a rotation plan to a large number of workers. However, when optimality is the goal, the GA could be used. When using GA-SA, the results are not improved, implying that the GA already gives a good solution quality.

In the last part of our analysis, we investigate the impacts of using job rotation to reduce the noise exposure burden of workers, while promoting employee cross-training. Without noise-safe job rotation, some employees are exposed to excessive DND. Although the horizontal skill is well-developed resulting in lower delay from continuous skill development, more delay is caused by boredom-induced dissatisfaction. When noise-safe job rotation is applied, the DND among workers is substantially reduced and more proportionally distributed. However, more production delays occurred from the interruption of skill development. Eventually, the delay from the lack of skill will lessen after employees have developed multi-skills to a certain point.

The proposed model is suitable for the case where workers are constantly exposed to noise hazards. The model can be modified to account for other occupational hazards. For variable-limit hazards, such as heat and fatigue, the workforce is treated as a group of individuals with different exposure tolerances. The characteristics of individuals, in terms of personal exposure tolerance to the hazards, need to be considered. A sensitivity analysis is performed in this study using various problem sizes. The parameters that affect the effectiveness of the proposed job-rotation approach include the skill learning and forgetting rates of workers and the effects of boredom on job satisfaction and productivity. The sensitivity analysis can be extended to investigate the impacts of these parameters on the effectiveness of noise-safe job rotation. Another important future research task is to conduct a case study to validate safe job-rotation models and algorithms in the literature. Based on the previous studies in our literature survey, the number of case studies is limited. In our future research, we will use a manufacturing industry case study to validate our model and problem-solving algorithms, to gain more insight into the possible impacts of job rotation.

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