A Research Framework for Optimizing Staggered Work-Rest Schedule for Construction Workers During the Pandemic

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Abstract

The COVID-19 pandemic represents the most significant global health emergency of the last several decades, resulting in the deaths of millions of people worldwide. The spread of COVID-19 among construction workers has been extremely high, with frequent clusters of COVID-19 cases related to construction sites. Workplace contact is considered the primary cause of these outbreaks. Many governments have suggested implementing staggered scheduling to maintain social distancing among construction workers, but specific staggered work-rest schedules for construction workers, in terms of start time, rest time, and rest duration, are still not available. Therefore, it is necessary to establish optimal staggered work-rest schedules to reduce the infection risk at construction sites. This study proposed a research framework to develop optimal work-rest schedules that can maximize the labor productivity of construction workers while minimizing contact between them. Two research tasks are proposed, including utilizing machine learning methods to estimate workers' maximum working duration and rate of recovery, and generating optimal staggered work-rest schedules by establishing mathematical programming models. The preliminary results have proved the feasibility of this research framework and laid a foundation for further research. The staggered work-rest schedule model proposed by this research framework could reduce infection risks for construction workers during pandemics as well as enhance the labor productivity of construction projects.

Keywords: *staggered work-rest schedule, workplace contact, labor productivity, COVID-19*

1. INTRODUCTION

The COVID-19 pandemic stands as the gravest global health catastrophe in recent decades, causing not only catastrophic effects on human health but also deeply impacting the global economy and social activities. Due to the limited feasibility of conducting construction activities virtually, the construction industry has been greatly impacted by the pandemic crisis. Compared to 2019, the total construction production in the United Kingdom decreased by 12.5% in 2020 (Office for National Statistics (ONS), 2021). In the United States, the gross domestic production (GDP) of the construction industry saw a decline of 26.5% in the second quarter of 2020 (Bureau of Economic Analysis (BEA), 2020). The transmission rate of COVID-19 among construction workers has been extremely high, nearly topping all other industries in 2019, and the risk of hospitalization due to COVID-19 is five times higher for construction workers compared to those in other sectors (Pasco et al., 2020). Many large-scale COVID-19 cluster outbreaks on construction sites have been reported, raising significant concerns about construction workers' health and safety.

Workplace contact is considered the primary cause of these construction site outbreaks (Pamidimukkala and Kermanshachi, 2021). Many governments have suggested the implementation of social distancing guidelines on sites to reduce the infection risk among construction workers. These guidelines include dividing frontline workers into different working groups; staggering the use of shared facilities; and staggering start, break, and finish times (Construction Industry Council (CIC), 2021). These recommendations introduce the concept of staggered work-rest schedules into the construction industry. However, adopting staggered schedules that adhere to social distancing guidelines may result in a decrease in the productivity of construction workers. The challenge lies in developing effective staggered schedules that can overcome the negative impact of social distancing regulations on construction labor productivity. Therefore, it is imperative to explore how to establish optimal staggered schedules in the context of the epidemic.

The objective of this paper is to propose a research framework for optimizing the staggered work-rest schedules for construction workers during the epidemic. The proposed optimized work-rest schedule can maximize the labor productivity of construction workers while minimizing the contact between them. This research framework includes two research tasks. First, machine learning methods are used to estimate construction workers' maximum work duration (MWD) and rate of recovery (ROR) based on consideration of work-related, environmental, and personal factors that can affect worker fatigue. Then, mathematical programming models and tailor-made solution algorithms are established to generate optimal staggered work-rest schedules. The staggered work-rest schedule outlined in this research framework can potentially decrease infection risks for construction workers during pandemics while boosting their productivity. This holds considerable significance in fostering safe, healthy, and efficient working environments in the construction industry.

2. LITERATURE REVIEW

2.1. Worker Fatigue in the Construction Industry

The key parameters required for constructing a work-rest schedule model include the maximum duration of work that a worker considers acceptable and the amount of rest time necessary for fatigue recovery. The impact of worker fatigue on work performance within the construction industry is well-documented, including decreased work quality, reduced labor productivity, and increased safety problems (Wang et al., 2023). Related studies have demonstrated that various factors such as work-related factors (job nature, work duration, workload), environmental factors (heat/cold stress, light, noise, elevation), and personal factors (age, gender, height, weight, work experience, sleep time, smoking and drinking habits) can significantly affect fatigue among construction workers (Yi et al., 2016; Zong et al., 2024).

Construction worker fatigue is usually assessed through subjective and objective measures. Subjective measures refer to individuals self-rating their fatigue level using fatigue assessment scales, such as Rating of Perceived Exertion (RPE) and Rating of Fatigue (ROF) (Umer et al., 2023). Objective measures typically involve physiological or biomechanical analyses, such as monitoring construction workers' cardiovascular and thermoregulatory indices (Umer et al., 2020). With the advancement of wearable sensing technologies, assessing fatigue among construction workers has become more convenient and accurate (Abuwarda et al., 2022).

Previous research on monitoring and predicting construction worker fatigue has mainly relied on conventional statistical methods, such as multiple linear regression (MLR) models. However, challenges arise due to the potential nonlinear relationships and the exceeding predictive capabilities of MLR models regarding worker fatigue and its influencing factors (Rowlinson et al., 2014). Consequently, several studies have shifted towards utilizing more sophisticated machine learning models that can detect previously unknown relationships in data by modeling nonlinearity and interactions, in order to tackle these complex issues and have achieved promising results (Anwer et al., 2023).

2.2. Work-Rest Schedule in the Construction Industry

Proper rest is considered an effective way for construction workers to recover from workplace fatigue. Therefore, it is recommended to establish optimal work and rest arrangements for workers to help enhance their, health, safety, and productivity. The design of work-rest schedules involves setting parameters such as work-rest frequency, work duration, and rest times (Hise et al., 2009). A variety of optimization techniques has been utilized to optimize the work-rest schedule in the construction sector, such as linear optimization, integer linear optimization, mixed-integer linear programming, and multi-objective mathematical programming (Yi and Wang, 2016 & 2017). For instance, Yi and Chan (2013) utilized the Monte Carlo simulation approach to explore the optimal work-rest schedule that would improve labor productivity in construction while reducing the effects of heat stress. Yi and Wang (2016) put forward a multi-objective framework for assigning construction workers, taking into account the dual goals of minimizing task completion time and reducing overall overexertion. Yi and Wang (2017) introduced a mixed-integer linear model designed to refine the scheduling of work and rest periods for construction workers in hot weather. These findings indicate that the productivity of construction workers can be greatly enhanced by implementing appropriate rest periods. Consequently, some governments have enacted regulations regarding workers' work-rest schedules. For instance, the Hong Kong Construction Industry Council (CIC) mandates that construction workers take a 30-minute break in the afternoon and an additional 15-minute break during the hot summer (May to September).

Current research underscores the importance of optimizing work-rest schedules for construction workers in terms of both safety and labor productivity. Previous studies in ergonomics and construction have established methods for measuring fatigue and exploring various optimization methods to simulate construction project progress. However, previous studies have primarily concentrated on work-rest schedules concerning the impact of heat stress, with minimal attention given to work-rest scheduling during epidemics in the construction industry.

3. RESEARCH FRAMEWORK

3.1. Estimate Maximum Work Duration (MWD) and Rate of Recovery (ROR)

Field studies will be conducted at various construction sites, and at least 250 construction workers will be involved. Each participant will be equipped with a heart rate (HR) sensor and a core body temperature (CT) sensor to record their real-time HR and CT data. The Rating of Perceived Exertion (RPE), rating from 0-10, will be used to assess the subjective fatigue level of the participants. Before the test, participants will undergo a 20-minute rest to stabilize their HR and CT. During this period, they will be asked to provide personal information, such as age, height, weight, work experience, clothing, sleeping time, smoking and drinking habits. They will then perform their routine work on the site until exhausted. Wearable sensors will measure their HR and CT values every 1 second. They will also report their RPE value every 5 minutes without interfering with normal work operations. An environmental monitor will be deployed to simultaneously monitor environmental parameters every 1 minute. The time from when participants start to stop working (the participant reports an RPE of 10) will be recorded as their MWD. They will then be placed on site for recovery, and their HR and CT data will be still monitored to calculate their ROR.

Each sample collected from a construction worker will contain personal information data, work-related data, physiological data, MWD, ROR, and environmental data. The MWD estimation model will be developed by establishing the relationship between MWD and the set of physiological, personal, work-related, and environmental factors. The ROR estimation model will be developed for ROR and the independent variables include physiological, personal, work-related, environmental factors, and rest durations. Prediction models for MWD and ROR will be built using supervised machine learning regression methods. A variety of machine learning methods such as support vector regression, gaussian process regression, random forest, and neural networks will be employed. The model that provides the greatest accuracy can be selected by comparison, so as to achieve the estimation of construction workers' MWD and ROR.

3.2. Develop Optimal Staggered Work-Rest Schedule Model

Utilizing the key parameters MWD and ROR estimated above, this study will then develop an integer programming model to refine the work-rest schedule for construction teams, including the start, break, and finish times, as well as the selection of the rest areas and meal places for each team. In the optimization process, the two objectives are to maximize the overall construction labor productivity of all work teams and minimize workplace contact between different teams. Construction labor productivity can be quantified by the time dedicated to productive tasks by workers. The time spent in the workplace beyond one's physical capacity, that is MWD, can be classified as non-productive time. In this study, a worker's productive time within a work session is determined as the minimum value of the MWD or the planned duration of work for that session. The daily productive time of a worker is calculated by adding up the productive times from all work sessions throughout the day. Workplace contact is determined by factors such as team numbers, team size, and the duration of contact in a shared facility.

The most common method used for addressing bi-objective optimization models is combining the two objectives through weighted scaling to reflect their relative importance (Bérubé et al., 2009), and the single-objective model can be converted into an integer program. However, converting the single-objective model into an integer program poses challenges, as generating all work-rest schedules is often not feasible, making it difficult to utilize integer-programming solvers to solve it. Therefore, a branch-and-price algorithm will be developed, where the "pricing" operator identifies a very small subset of work-rest schedules likely to include an optimal solution, eliminating the need to enumerate all possible schedules. The "branching" operator ensures the optimal solution within this subset.

3.3. Preliminary Results

(1) Participants and instruments

Currently, three field studies have been conducted at three construction sites in the Anhui and Guangdong provinces of China. To date, a total of 81 healthy construction workers have been recruited from these construction sites to participate in data collection. The average age and Body Mass Index (BMI) of the participants were 51.8 years (SD ± 8.02) and 23.8 kg/m^2 (SD ± 3.99), respectively. Participants were asked to ensure they did not have a history of musculoskeletal, neurological, or cardiovascular diseases, and consent was obtained from all participants before the experiment began. The personal information of the participants was collected through a questionnaire survey. Physiological sensors were used to record the participants' HR (Polar H10, Finland) and CT (CALERAresearch, Switzerland) per second. The Borg CR10 Scale, a 10-point scale with anchors extending from 1 (very very easy) to 10 (maximal exertion), was used to assess workers' RPE. In addition, an environmental monitor (QUESTemp 36, Australia) was utilized to measure environmental parameters.

(2) Data processing and analysis

Raw HR and CT data collected through physiological sensors were preprocessed using Savitzky Golay filters and moving average filters to remove the artifacts in the signals. The continuous HR and CT signals are then divided using a moving window with an overlap of 50% to reduce errors caused by transition state noise (Su et al., 2014). This resulted in the formation of a total dataset of 35394 physiological data points. For the application of machine learning methods, feature extraction of the collected data is required. A total of 14 features related to work, personal, physiological, and environmental factors were identified for subsequent data analysis, as shown in Table 1.

Table 1. Extracted features for machine learning

Types	**Variables**
Work-related features	Job nature; Work duration; Rest duration
Personal features	Age; Body mass index (BMI); Work experience; Clothing; Sleeping time; Sleeping habit; Drinking habit; Smoking habit
Physiological features	Heart rate (HR); Core body temperature (CT)
Environmental features	Wet bulb globe temperature (WBGT)

Among machine learning methods, tree-based algorithms are an important branch and are considered one of the most commonly used supervised learning methods (Zhang et al., 2024). Tree-based methods can effectively handle large-scale data regardless of data type, and compared with some linear models, tree-based methods do not need for complex feature preprocessing (Rashid et al., 2022). Therefore, this study first attempts to use one of the tree-based machine learning models, the eXtreme Gradient Boosting (XGBoost), to preliminarily predict the fatigue level of construction workers (i.e. RPE), laying a foundation for subsequent prediction of workers' MWD and ROR.

(3) Preliminary results

XGBoost machine learning model was used to analyze the collected samples. The model underwent training with a random selection of 80% of the samples, with the remaining 20% used for the testing process. The performance measurements confirm that this model is a well-fitted prediction model, as shown in Figure 1. R^2 is an important indicator to test the validity of the prediction model, the closer its value to 1, the greater the concordance between the measured and predicted outcomes. The R^2 value (0.994) obtained in this model shows that the predicted model can explain at least 90% of the measured data. In addition, Mean Absolute Percentage Error (MAPE) is a reliable measure for comparing the residual error of individual data points against the observed or target value. A lower MAPE value indicates a higher accuracy of the model's performance. The MAPE value obtained in this model was 1.4%. Root Mean Square Error (RMSE) is another statistical indicator that measures the discrepancy between observed and predicted values by computing the square root of the average squared differences. The lower the RMSE value, the higher the accuracy of the model's predictive capability. The RMSE value obtained in this model was 0.099. All these indicators imply that the model has good prediction performance.

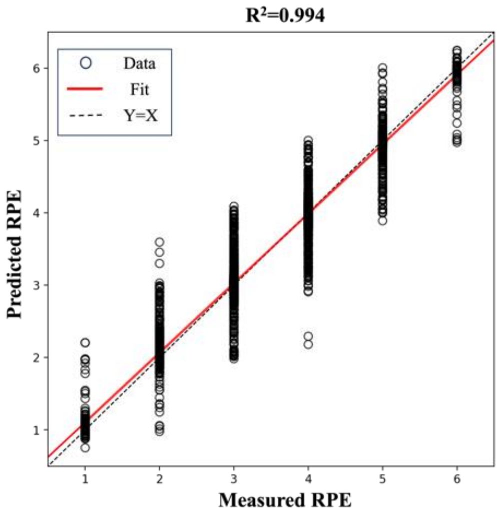

Figure 1. Relationship between the measured and predicted RPE values in the XGBoost model

The above results also show that the selected input features are important factors affecting the fatigue of construction workers, and can effectively help to achieve accurate prediction of worker fatigue. This suggests that these features will also be of high importance in the subsequent predictions of MWD and ROR, which are related to construction worker fatigue. In the subsequent prediction of MWD and ROR, the XGBoost model can continue to be used, and on this basis, other machine learning methods can be further attempted to compare and select the best-performing prediction model.

4. CONCLUSION

Construction is the economic backbone of most countries and one of the most labor-intensive industries. However, this industry is particularly vulnerable to COVID-19. To reduce the infection of construction workers by reducing the transmission in the construction site, a research framework for optimizing staggered work-rest schedules for construction workers during the pandemic is proposed. In the short term, this research framework can contribute to a safer, healthier, and more productive workforce. In the long term, this research framework can have positive implications for construction workers, contractors, the construction industry, as well as the government, helping to encourage workers and employers to maximize labor productivity and protect worker health and safety by reducing cross-infection on sites. In addition, in the post-pandemic future, the design of staggered work-rest schedules can also serve as an effective means to increase labor productivity, such as in crowded workplaces. This is of great value in creating a safe, healthy, and productive work environment. The preliminary results have proved the feasibility of this research framework and laid a foundation for further research. However, this research framework also has some limitations. This framework did not comprehensively assess labor productivity by using labor hours as the input unit and the physical quantity as the output. Instead, it only measured the time utilization of workers as part of construction productivity measurement. Additionally, certain construction tasks, such as concrete pouring, may surpass workers' maximum work duration. Therefore, further research is warranted on designing work-rest schedules for these tasks.

5. ACKNOWLEDGMENT

The research presented in this paper is funded by a grant from the Research Grants Council of the Hong Kong Special Administrative Region, China (RGC Project Number 15200823).

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