# Construction worker fatigue load management using IoT heart rate sensing system

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**Abstract**

**Many studies consider excessive fatigue as one of the reasons for accidents among construction workers, especially in special hazardous work environments such as working at heights, heavy physical labor, and confined spaces. Unfortunately, due to factors such as complex environments, unstable equipment, and frequent movement of workers, there is little research on safety management of confined spaces and fatigue loading of construction workers in the construction industry. Therefore, this study developed an Internet of Things (IoT) heart rate sensing system, which has been verified in the real field and can be applied to the physical and mental health management of tunnel workers in the construction industry. In addition, a fatigue interval fitting model for construction workers was established by applying the percentage of heart rate reserve (%HRR). The maximum value of the anticline point %HRR in the model was defined as the fatigue alert value for construction workers, which facilitates project managers to monitor the abnormal conditions of workers' physiological load in a timely manner.**

**Keywords –**

**Worker Fatigue Load; Confined Space; Internet of Things Heart Rate Sensing System; %HRR**

## 1 Introduction

The construction industry employs about 7% of the global employment, and 100,000 workers die on construction sites every year, which is about 35% of the global occupational fatalities [1]. Many studies have shown that occupational accidents in the construction industry are associated with overwork and fatigue among workers, as inattention may affect their awareness of environmental hazards or cause accidents during the operation of construction machinery [2-4]. In previous studies, heart rate (HR) was commonly used to measure worker fatigue in the construction field [5]. Some studies have also used relative standards to measure the workload or training load of an individual, such as the percentage of heart rate reserve (%HRR), %VO2max, etc. [6-8]. The relative standard focuses on the management of the output of the percentage of body energy relative to the load, which is more conducive to the precise management of an individual's physical and mental conditions.

With the development of wearable devices, more and more physiological parameters can be easily collected [9], including electromyography (EMG) [10,11]. Electroencephalography (EEG) [12,13] and wrist-worn photoplethysmography (PPG) devices [14-16]. In these techniques, EMG and EEG are weak bioelectrical signals that are susceptible to interference from a variety of noises. In addition, they are invasive in nature and lack convenience [17]. The wristband PPG heart rate sensor not only can monitor the heart rate of workers in real-time but also does not cause discomfort to the staff, so it has more potential [18].

Despite these advances, the collection of physiological parameters and personalized fatigue management is still a challenge due to complex environments, unstable equipment, and frequent worker movement, and there is a lack of a basis for judging the safety of fatigue load management for special hazardous operations such as confined spaces in the construction field. Therefore, this study develops an Internet of Things (IoT) heart rate sensing system for the limited space in the construction industry. In addition, based on the physiological values of construction workers, this study establishes the coordinate axes with the horizontal axis as the cumulative percentage of heart rate reserve (HRR) and the vertical axis as the cumulative percentage of working time [CPWT] (%) to establish a fatigue interval fitting model for construction workers. It defines the maximum value of the hyperbolic point in the model as the fatigue alert value of the construction workers, which is convenient for project managers to monitor the abnormalities of the workers' physiological loads in a timely manner.

Unlike previous studies, the heart rate sensing system of the construction industry's Internet of Things (IoT) can be used for continuous sensing during the whole working day, which overcomes the complex environmental interference in the submerged shield tunnel and achieves stable data transmission. In addition, the sampling frequency, calculation time window, and measurement verification method of this study are also different. In the data analysis stage, instead of adopting the medical concept of Field resting heart rate (FRHR), this study calculated the FRHR at the construction site and then calculated the %HRR. Python was used to fit the relationship between cumulative heart rate reserve consumption percentage (% HRR) and working time percentage. The coefficient of determination R^2(R-squared), root mean squared error (RMSE), and mean absolute error (MAE) of the fitted curve were used to evaluate the results of the regression curve equation, and then to find out the anticline of the cumulative curve of each day, and the largest anticline of %HRR was used as the warning value for this worker. The maximum anticline %HRR is used as the warning value for this worker.

## 2 Literature Review

### 2.1 Physiological indicators of workload in the construction industry

The causes of excessive workload and fatigue are very complex. Some studies have used relative physiological indicators to measure an individual's workload, focusing on the management of the output of the percentage of the individual's physical capacity close to the load, which is more conducive to the measurement of individualized fatigue in laborers and the need for safety management in the workplace, for example, emotional heart zone, the percentage of heart rate reserve, and %VO2max [5-8], Among them, %HRR is considered suitable for assessing the physical demand of labor tasks and applied to measure the workload of workers [19,20]. However, few studies have defined the specific safety interval of %HRR for construction workers. Chen & Tserng (2022) considered that the %HRR of workers and the percentage of cumulative working hours show an S-curve relationship, and its distribution location and anticurve point have the significance of the safety management of workers' load [21]. In this study, the concept is continued, and a fatigue interval simulation model is established to find out the specific value of the anticurve point of %HRR as the fatigue warning value of construction workers, which can also get the safety interval of the workload of construction workers.

### 2.2 Development of IoT real-time heart rate sensing systems

The Internet of Things (IoT) heart rate sensing system has only begun to be practically applied to actual construction sites in recent years, including intelligent sensing, cloud-based IoT technology, and real-time heart rate monitoring and management using big data. The sensing data collection and processing has also expanded from hours and minutes to continuous sensing technology [20,22]. However, Anwer et al. (2021) argued that the challenge of using real-time physiological measures to assess physical fatigue in construction workers is the limitation of the validity of the physiological values used to determine fatigue, and there is a severe lack of information on fatigue due to data omission. [23].

Currently, there is still a lack of physiological sensing systems for the monitoring and management of tunnel workers, such as access control, localization in tunnels, and display of vital signs. Therefore, this paper evaluates the development of a physiological sensing system suitable for long-term monitoring functions and conducts system validation in the confined space of a submerged shield tunnel site.

## 3 Methodology

This research mainly consists of four main phases as depicted in Fig. 1: (1) Data Acquisition Overview (2) Design of IoT heart rate sensing system (3) Reserve heart rate percentage (%HRR) calculation (4) Personal Safety Interval Fitting Model.

### 3.1 Data Acquisition Overview

Tunnel construction is a high-risk construction operation with more stringent labor safety requirements. This study was conducted with the consent of the construction company under the condition of not interfering with the construction workers' work. The test subjects were all the construction workers in the construction area, working from 07:00 to 19:00, and their heart rate was monitored and recorded throughout the whole process—recruitment of test subjects: 23 people, all male. Due to the demand of project tasks and personnel mobility, not all 23 workers were on the job or recorded continuous heart rate data, so in this study, only P1, P2, P3, P4, P5, P6, P8, P9, P11, P13 will be used, a total of 10 workers' data, as shown in Table 1.

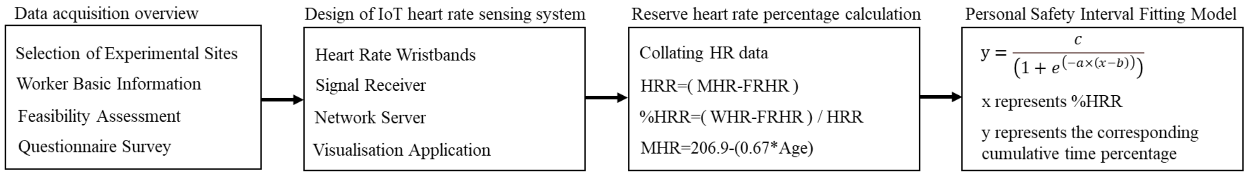


Figure 1. The methodological flow chart of this study

Table 1. Basic data table of construction site testers

| Subject | Age | Height cm | Weight kg | Experience Years | Cardiovascular Disease | Smoking Years | Drinking Habit | Conscious Fatigue |
|---|---|---|---|---|---|---|---|---|
| P1 | 36 | 179 | 86 | 10 | N | 0 | N | N |
| P2 | 28 | 164 | 85 | 5 | N | 14 | Y | Y |
| P3 | 41 | 172 | 83 | 2 | N | 20 | Y | N |
| P4 | 45 | 178 | 85 | 19 | N | 31 | N | NS |
| P5 | 45 | 161 | 74 | 5 | N | 20 | Y | NS |
| P6 | 26 | 172 | 73 | 1 | N | 12 | N | Y |
| P8 | 35 | 168 | 90 | 2 | N | 25 | Y | NS |
| P9 | 23 | 165 | 43 | 1 | N | 10 | Y | Y |
| P11 | 42 | 168 | 60 | 10 | Y | 10 | Y | N |
| P13 | 31 | 186 | 71 | 6 | N | 17 | Y | NS |

## 3.2 Design of IoT heart rate sensing system

### 3.2.1 Sensing system equipment and specifications

The environment in the confined space of the construction industry is complex, with poor quality network signals, darkness, humidity, loud noise, high mobility of workers, frequent job rotation, and high difficulty in mechanical operation. In the view of these characteristics, this study develops sensing devices and constructs an Internet system suitable IoT-PPG for this field in order to increase the feasibility and acceptance of physiological sensing device applications. The equipment and specifications of the heart rate sensing network system in this study are shown in Table 2.

Table 2. Heart Rate Sensing System Equipment and Specifications

| Device Name | Functional Specifications |
|---|---|
| Heart Rate Wristbands | • Detection frequency > 500<br>• Signal Frequency >10 times/sec.<br>• Power Durability >12 hours<br>• Waterproof rating IP 67 |
| Signal receiving and transmission equipment | • BLE Router: Raspberry Pi 3B+<br>• Low Power Bluetooth Transmission<br>• Simultaneously receiving 20 Wristbands<br>• 100Mbps Ethernet interface |
| Server Hosting Application Software | • Ubuntu 16<br>• Java Script<br>• HTML |

### 3.2.2 Planning of sensing systems in actual field

The experimental field of this study is the construction site of the tunneling project, in order to make the sensing bracelet broadcasting signal can be received smoothly, the system adopts the Bluetooth BLE V4.2 transmission standard and configures the signal receiving equipment in the construction location where the personnel is permanently stationed, and aims at the system data coverage rate of more than 80%. According to the characteristics of the construction operation of the shield project, this study divides it into three sensing areas, A, B, and C. It allocates eight signal-receiving devices, as shown in Fig. 2, which are as follows: A. Ground working area, including four receiving sensors for a workshop, rest standby, machine maintenance, and material lifting; B. Working shaft area, with one receiving sensor at the bottom of the shaft; and C. Tunneling area, including three receiving sensors for the front, middle, and tail sections of the shield machine. C. Tunnel dull area, including three receiving sensors for the front, middle, and tail sections of the potential shield machine. As shown in Fig. 3, it is a worker wearing a heart rate wristband and a Bluetooth receiver transmitter in a shield tunnel.

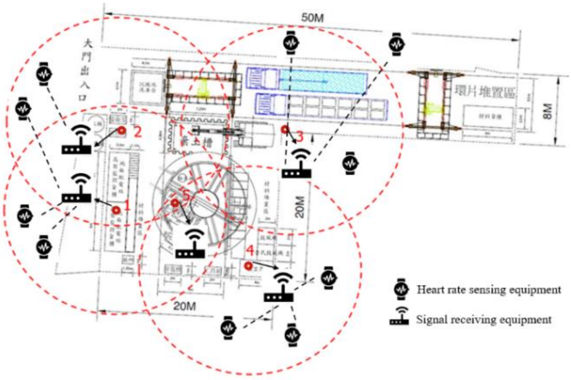


Figure 2. System equipment configuration plan of ground operation area A and working well area B

|  |  |
|---|---|
| a. Bluetooth receiver and transmitter in shield tunnel | b.Workers wearing heart rate wristbands in the shield tunnel |

Figure 3. Subjects wearing wristwatches work in a small shield tunnel environment in the experimental field

### 3.3 Reserve heart rate percentage (%HRR) calculation

In this study, based on the theoretical development of cardiovascular loads (CVL) [24] and heart rate reserve (HRR) [7] [8] [25], the PPG heart rate was used as the basis for calculating the real-time %HRR index value, which reflects the degree of personal physical output of construction workers. The %HRR index value reflects the degree of individual energy output of construction workers and serves as an indicator for the real-time management of the workload of construction laborers. The significance of the %HRR index refers to the rate of depletion of personal heart rate reserve, and the higher rate of depletion indicates a higher workload, and the related calculation equations are shown in (1) and (2):

$$HRR = (\,MHR - FRHR\,) \quad (1)$$

$$\%HRR = (\,WHR - FRHR\,)\,/\,HRR\, *\, 100\% \quad (2)$$

MHR=206.9-(0.67*Age), Maximum heart rate value,bpm. FRHR= Rest heart rate in the construction site area, bpm. WHR= Rest heart rate in the construction site area, bpm. The estimated maximum heart rate was calculated using an age-corrected estimation formula proposed by Jackson et al. (2007) [26]. The resting heart rate was measured using the field resting heart rate (FRHR) [21].

### 3.4 Personal Safety Interval Fitting Model

A sigmoid function, also known as the Logistic function fitting curve, is a function that maps the independent variable to a function between 0 and 1. It is often used to categorize a problem or to represent the growth trend, with formulas such as (3), [27] [28].

$$y = \frac{c}{(1+e^{(-a\times(x-b))})} \quad (3)$$

Where x represents %HRR, y represents the corresponding cumulative time percentage, a represents the control of the growth rate of function, b represents the center point of the function and the slope of the sigmoid function, and c represents the upper limit value of y when x approaches infinity.

This study used Python to fit the relationship between cumulative heart rate reserve consumption percentage (% HRR) and working time percentage. The same worker was statistically counted for more than seven days, and the data were organized into a 5-minute average %HRR time series. The coefficient of determination R^2(R-squared), root mean squared error (RMSE), and mean absolute error (MAE) of the fitted curve were used to evaluate the results of the regression curve equation, and then to find out the anticline of the cumulative curve of each day, and the largest anticline of %HRR was used as the warning value for this worker. The maximum anticline %HRR is used as the warning value for this worker.

## 4 Results and Discussion

The results of the fitted regression curves for the safety interval of fatigue loads for construction workers in this study are discussed. Taking the fitting results of P1, P4, and P9 workers as an example, they have continuous heart rate data for more than seven days, and their job types are construction site managers, crane operators, and trolley drivers.

The main task of P1 is site management, and the %HRR data are simulated for nine days. The coefficient of determination R^2 is above 0.97, which is highly interpretable, and the root mean square error (RMSE) and the mean absolute error (MAE) are less than

5%, which makes the regression curves highly reliable. The maximum %HRR reversal point occurred on November 9, P1_1109, with a %HRR of 36.4%. The overlapping curve area is bounded by P1_1101, P1_1103, and P1_1109, as shown in Fig. 4, which can be regarded as the safety zone of fatigue load for P1's past work.

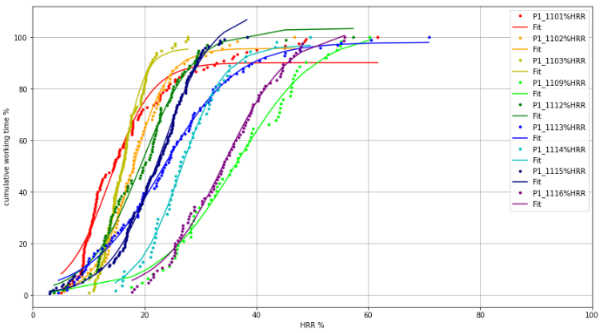


Figure 4. Fatigue Load Data Point Plots and Fitting Curves for Worker P1

The main work item day of P4 is the overhead crane operation, and 13 days of monitoring %HRR data are simulated. The coefficient of determination R^2 all falls above 0.98, with high interpretation power, the root mean square error RMSE and the mean absolute error MAE of %HRR obtained from the simulated curves are less than 4%, and the regression curves have a high degree of feasibility. The maximum %HRR anticlip occurs in P4_1102 on November 2, with a %HRR of 36.4%. The overlapping curve area of each day is bounded by P4_1109, P4_1112, P4_1102 and P4_1107 as shown in Fig.5, and this area can be regarded as the fatigue load safety zone of P4 in the past work.

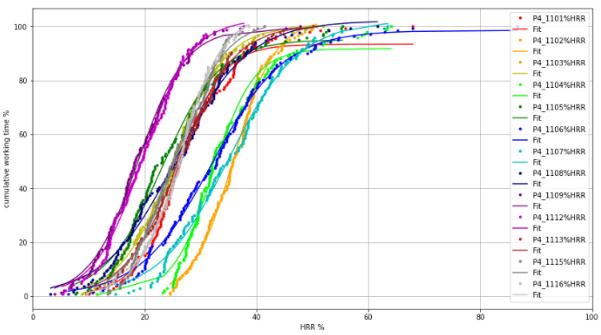


Figure 5. Fatigue Load Data Point Plots and Fitting Curves for Worker P4

The primary working day of P9 is cart driving, which belongs to the category of mechanically operated work with lower loads. Eleven days of %HRR data were simulated, and except for one day, P9_1106, which has a relatively small amount of data, with a coefficient of determination of R^2 of 0.94, an RMSE of 6.5%, and an MAE of 5.4%, and the regression result is a little bit lower, most of the other days' R^2 falls above 0.97, which is of high interpretative power. The root mean square error (RMSE) and the mean absolute error (MAE) of %HRR obtained from the fitted curves are mostly less than 4%, which means that the regression curves have a high degree of reliability. The most significant %HRR inversion point occurs on November 12, P9_1112, with a %HRR of 40.4%. The overlapping curve area of each day is bounded by P9_1106 and P9_1112, as shown in Fig.6, and this area can be regarded as the fatigue load safety area of P9 in the past work.

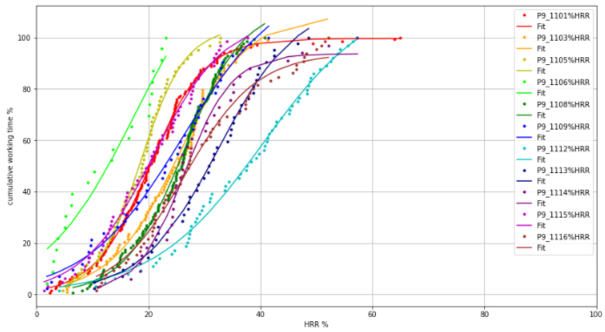


Figure 6. Fatigue Load Data Point Plots and Fitting Curves for Worker P9

## 5 Conclusion

This study develops a customized wearable IoT-PPG heart rate bracelet and wireless sensing system, which can be used for continuous sensing during the whole working day. It is field-proven to be applied to the physical and mental health and safety management of tunnel workers in a submerged tunnel, which is better than traditional tunnel personnel management.In addition, in this study, the accumulated physiological values of workers were used to synthesize the equation $y = \frac{c}{(1+e^{(-a\times(x-b))})}$, which is composed of three unknowns, using Python. This equation has a high explanatory power and a low error, and it can be used to superimpose the cumulative curvilinear inversion point of %HRR over a few days as a warning value to establish a model of the safety zone for workers' fatigue load in the confined space of the construction industry. When the %HRR of a worker's future work exceeds the warning value, it is possible to pay appropriate attention to the worker's workload situation and adjust the working hours to reduce the occurrence of fatigue, which can be used as a reference for future related studies.

In the future, the data processing algorithm of this study can be extended and applied to other workplaces with harsh environments such as high temperature, high altitude, etc., to develop a logistic regression model for continuous %HRR workload prediction so as to establish the prediction of workers' residual physical capacity and the management of precise working hours.

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