An Explorative Context-aware Machine Learning Approach to Reducing Human Fatigue Risk of Traffic Control Operators

Abstract

Traffic control operators are usually confronted with a high potential of human fatigue. Existing strategies to manage human fatigue in transportation are primarily by undertaking prescriptive "hours-of-work" regulations. However, these regulations lack certain flexibility and fail to consider dynamic fatigue-inducing factors in the context. To fill this gap, this study makes an explorative first step towards an improved approach for managing human fatigue. First, a fatigue causal network that can adequately represent the context factors and their dynamic interactions of human fatigue is proposed. Moreover, to overcome its problem of high dimension sparse matrix, a novel method based on the artificial immune system and extreme gradient boosting algorithm is introduced. A case study of vessel traffic management showed that the model could predict the fatigue level with high accuracy of 89%. Furthermore, to lower the risk of fatigue occurrence, a novel scheduling algorithm is also provided to adaptively arrange work for operators considering individual differences and work types. The study results showed that 27% of operators could be rearranged to reduce the possibility of human fatigue. Nevertheless, considering that more than half of operator were still fatigue in the case study, human fatigue is still a critical problem. It is hoped this research, as an explorative study, can offer insightful references to traffic management authorities in their safety management process with better operation experience.

Keywords: adaptive work arrangement; context-awareness; machine learning; human fatigue prediction; traffic control operators

1. Introduction

Traffic control operators (TCOs) are people who monitor real-time traffic and provide instructions or advice to traffic operators, including pilots, drivers, and train drivers. TCOs' work includes intense information processing and passive monitoring instead of active control [1, 2]. Besides, they carry out a clock in shift work to guarantee traffic smoothness, mitigate delays, and improve the safety of the traffic network. Such working condition interrupts their sleep-wake cycle and degrades sleep conditions, resulting in a high potential of human fatigue [3]. Human fatigue is a critical risk, as it causes 15 to 20% of existing transportation accidents, affecting all modes of transportation (e.g. road traffic, maritime transport) [4-6]. For instance, the National Highway Traffic Safety Administration (NHTSA) reported that drowsy drivers had caused almost 100000 crashes per year in the United States of America [7]. Moreover, on the railroad, it was found that "operator fell asleep" had often been a contributing cause of critical casualties [8], to name a few. Organizations and researchers have advocated work schedule improvement as the primary solution to reduce risks of human fatigue [9] and improve human performance [10]. They increasingly rely on biomathematical fatigue models to assess the likelihood of human fatigue with a given work schedule, as well as to manage the impact of shift design [9].

Those emerging fatigue models are not adequate for TCOs due to the following challenges. First, existing models mainly focused on time effects [9] and paid insufficient attention to dynamic working conditions. Working conditions of TCOs vary with vehicle types, traffic density and weather conditions [11], which usually induce dynamic workload on TCOs rather than a stable workload assumed. Second, few models consider individual differences in response to fatigue-inducing factors. In fact, due to differences in personality, age, experience, etc. [9], one may experience a dramatically different level of human fatigue, comparing with others under the same working conditions [12].

Meanwhile, recent studies have shown the necessity and promising benefits of considering contextual information in assessing human fatigue [7, 13, 14]. Nevertheless, it has been scarcely reported in the context-aware fatigue management area, and several issues still need to be further addressed:

1) What is the contextual information that presents the dynamic working conditions and individual differences exhibited by TCOs?

2) How to deal with numerous and inter-related factors involved in the contextual information?

3) What is the appropriate work arrangement that could reduce the risk of human fatigue?

For answering these questions, the authors define human fatigue and the scope of this study first. Some studies mentioned that there is no clear and widely agreed definition of human fatigue [13]. In 2015, Phillips [15] reviewed the definitions of human fatigue and proposed a whole definition: *Fatigue is a suboptimal psychophysiological condition caused by exertion…* This whole definition tries to describe all causes of human fatigue, resulting in too much information required for establishing a whole fatigue model. Inspired by this whole definition, this study limits the scope and defines fatigue as a suboptimal physical, emotional, motivational, and cognitive condition caused by a prolonged period of exposure to task-related stimuli. Besides, the effects of task-related stimuli would be aggregated or mediated by individual resilience, such as experience, age, and gender [16]. With this definition, this work aims to contribute to the infertile research area of TCO fatigue and safety by establishing a context-aware fatigue management approach for TCOs. The causal factors that existed in the contextual information are analyzed first and represented by a novel fatigue causal network. Then two main modules are developed, *fatigue prediction module* for assessing human fatigue based on context factors, and *work arrangement module* for arranging each operator to his/her appropriate work sector, respectively.

The rest of this paper is organized as follows. Section 2 discusses the existing human fatigue models, context-aware management techniques and machine learning methods in human fatigue management. Section 3 describes the causal factors of human fatigue captured in the contextual information, as well as a novel way to represent these factors. Followed by this, a proposed context-aware framework, fatigue prediction module, and work arrangement module are reported in Section 4. Section 5 presents a case study to validate the proposed approach, and a comparative research study is further conducted to depict its superiority among existing methods. At last, Section 6 outlines the main contributions and limitations of this work and highlights the potential future directions.

2. Literature review

This section summarizes relevant literature from two aspects, namely *fatigue model*, *context-aware management*, and *machine learning methods in human fatigue management*.

2.1 Fatigue model

The existing fatigue models focus on circadian rhythm, using working time and sleep time as inputs. In the early 1980s, Borbély [17] proposed a two-process model, Processes S and C to understand better and manipulate sleep. Fatigue is generally related to insufficient sleep and prolonged work [18], hence many efforts have been made to broaden the applications of the two-process model [19] and extended it to fatigue management [20]. The extended models have been widely used in civil aviation and nuclear power industries [19-21]. Dawson et al. [9] reviewed a series of theoretical models of human fatigue. They indicated that these bio-mathematical models express work patterns as a sequence of work and non-work periods and then use the circadian timing to predict fatigue [20].

These fatigue models heavily rely on using hours-of-work as inputs. More factors should be considered to achieve reliable results of human fatigue prediction for traffic operators [22].

Recent research works have claimed that integrating causal factors with circadian rhythm would be beneficial in managing human fatigue [7, 13, 23]. Strahan et al. [13] recommended companies to predict human fatigue based on organizational influence and occupational stress. Ji et al. [7] suggested investigating the dynamic aspects of human fatigue by considering various casual factors.

Despite these contributions, limited studies pay attention to investigate context data of human fatigue systematically. It is expected that the context-aware techniques can be promising and hence summarized below.

2.2 Context-aware management

The complex interactions among fatigue-inducing factors highlight the necessity of context-aware fatigue management other than relying solely on the hours-of-work [11]. In general, the context includes information about the present status of any entity in the environment. The goal of context-aware management is to acquire and utilize context information to provide appropriate services to specific people at a particular time [24, 25].

Some context-aware techniques have already been proposed [24, 26-29] and the activities on context-aware systems seem to have been increasing dramatically in recent years. For instance, Chang et al. [30] predicted taxi demand distributions using time, weather and taxi location. Ravi et al. [31] developed context-aware battery management by processing user's location traces and call-logs. Braunhofer et al. [26] developed a context-aware recommender system to generate recommendations based on weather conditions and places of interest.

A considerable number of studies have shown that context-aware techniques could improve system performance [24]. Nevertheless, limited studies investigated the potentials of developing context-aware fatigue management, let alone one in the transportation fields.

2.3 Machine learning in human fatigue management

In recent years, various machine learning approaches including random forest [32], decision tree [33, 34], AdaBoosted decision tree [35], and support vector machines (SVM) [36, 37] have been applied in human fatigue management. Tango and Botta [36] investigated the performances of SVM, linear regression, and neural network on detecting visual distraction based on vehicle dynamics data. They found that SVM outperformed all the other machine learning methods. Kamalian et al. [35] tested the performance of k-nearest neighbor, decision tree and SVM in estimating the human user's score. Among those machine learning approaches, SVM is most widely used in existing literature related to human fatigue management. Nevertheless, it cannot thoroughly address the problem of great diversity in human factors data [35]. The diversity in human factors data was caused by the diverse causal factors and great individual difference. Considering this, the authors proposed to incorporate an artificial immune system (AIS) and extreme gradient boosting algorithm (XGBoost) algorithm for human fatigue management.

AIS is a technique that simulates the biological immune system, which is adaptive and self-organizing [38]. It has many useful features, such as its ability to adapt and to learn from examples and its memorization and generalization capabilities. With these functions, the AIS has been successfully used in various fields, and it has even shown better performance than artificial neural network fuzzy systems and other approaches [39]. Considering the diverse casual factors of human fatigue, adaptive AIS is an appropriate method to preprocess the fatigue data. Besides, the fatigue data suffer from the problem of significant individual difference. Hence, the XGBoost algorithm is used to predict human fatigue. Primarily, it uses an ensemble technique where new models are added to correct the errors made by existing models. Models are added sequentially until no further improvements can be made [40]. Owing to this attribute, XGBoost has found to be a suitable way to handle data with individual differences [41].

3. Network-based fatigue model

This section provides a discussion in collecting and representing context factors of human fatigue. Grandjean [42] suggested considering human fatigue as the level of a liquid in a container. Many factors such as the surroundings, work factors, psychic factors, health and wellness fill this container and lead gradually to the state of human fatigue. Specifically, the surroundings include illumination, climate, and noise. Work factors are the intensity and length of manual and mental work. Psychic factors are responsibility, worries, conflicts. Health and wellness are assessed by illness, pain, and eating habits. Recovery is the only outflow from the container. Based on his study, the context factors of human fatigue are investigated and further classified.

3.1 Context factors of human fatigue

In the authors' previous study [16], it has been found that there are four main fatigue-inducing factors, namely, *environment factors, working conditions, circadian rhythm,* and *individual resilience*. Hence, the causal factors of human fatigue could be represented as $\{E, W, C, I\}$, as shown in **Figure 1**. E is a group of environmental factors, including the factors involved in the environment. In the context of traffic control, factors such as weather conditions, light level, temperature, visibility, and humidity could be considered as environmental factors. W is a group of working condition factors that are involved in a specific task, such as operation type, workload, and traffic density. C includes factors that affect circadian rhythms, such as time zone, time on task and work shift. Lastly, I refers to the factors which affect a person's response to the other three factors, and it has been found that personalities, experience, gender, and age would affect the experience of fatigue [16].

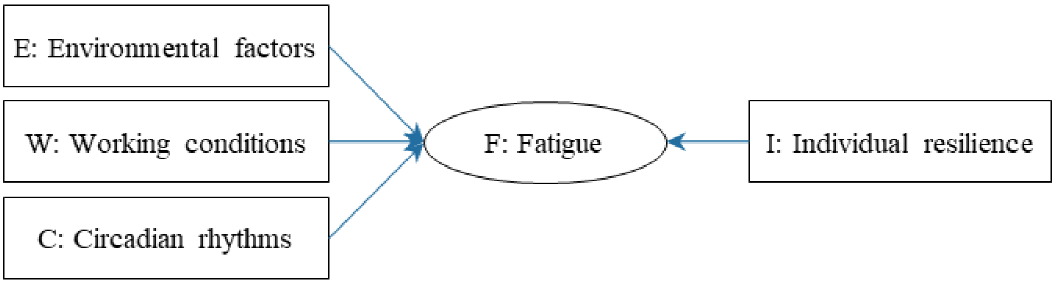

Figure 1. The causal factors of human fatigue

3.2 Fatigue causal network representation

Conventionally, $\{E, W, C, I\}$ can be represented as $CF = \{C_1, \dots, C_H\}$, where CF refers to all these causal factors of human fatigue, as shown in **Figure 2(a)**. There are significant correlations among fatigue-inducing factors [43]. Nevertheless, the traditional representation fails to consider the inter-relations among causal factors.

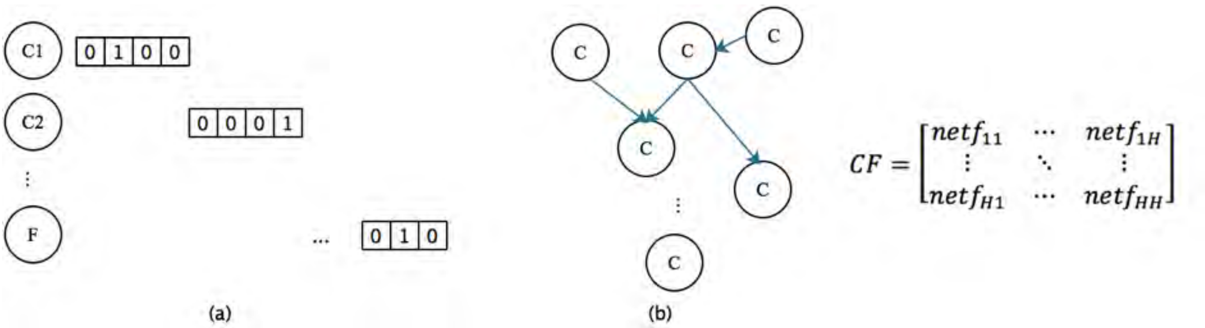

Figure 2. Causal factors (CF) representation: (a) conventional causal factors representation; (b) fatigue causal network representation

Causal networks have been used to deal with problems of different domains such as philosophy, health and environment and tourism [44]. Principally, a causal network can be used to express the inter-relationships among causal factors. Hence, instead of using the conventional representation of causal factors, a novel fatigue causal network representation is proposed in this work, as shown in **Figure 2(b)**, where

$$CF = \begin{bmatrix} netf_{11} & \cdots & netf_{1H} \\ \vdots & \ddots & \vdots \\ netf_{H1} & \cdots & netf_{HH} \end{bmatrix} \quad (1)$$

$$\text{For } h \neq j, netf_{jh} = \begin{cases} 1 & netf_j \ has \ effects \ on \ netf_h. \\ 0 & netf_j \ has \ no \ effects \ on \ netf_h. \end{cases} \ h,j \ \in [1, H]$$

$$\text{For } h = j, \qquad netf_{hj} = C_h$$

Each column of *CF* is a principal eigenvector of the effects of the jth element on the hth element. For h=j, $netf_{hj}$ refers to the value of the h^{th} node.

Though fatigue causal network brings some advantages, several challenges are induced in modeling human fatigue. Firstly, the causal network produces high dimension sparse matrix. It enlarges the dimension from N to $N \times N$, and this high dimension will result in increased computing time. Besides, using the high dimension matrix as an input of the fatigue prediction model will require a large amount of training data. Secondly, the heterogeneity of causal factors should also be addressed, including both qualitative variables and quantitative variables.

4. Context-aware fatigue management

Based on the proposed fatigue causal network, a context-aware machine learning approach is proposed to reduce the risk of human fatigue by providing appropriate work arrangements for a particular group of people at a specific time. Since the traffic control operations vary with traffic patterns, traffic amount and vehicle types, operators of different work sectors may suffer from different levels of human fatigue. Therefore, this study intends to arrange specific operators to their appropriate work sectors based on the fatigue causal network. Generally, it is almost impossible to make a work arrangement, which makes all operators are working at their best states, as some work sectors are challenging for all operators. Hence, this study aims at reducing the average fatigue level of a group working in the same environment instead of individuals. To achieve this aim, the authors predicted fatigue of each operator separately and then provided a suitable work arrangement to reduce the average fatigue level of the group.

4.1 Framework of context-aware fatigue management

The proposed context-aware fatigue management has two main parts, namely AIS and XGBoost-enabled fatigue prediction（AIS-XGBFP）and adaptive work arrangement, as shown in **Figure 3**. A fatigue causal network represents context information, including working conditions, environment, circadian rhythm, and individual resilience. Based on this, an AIS and XGBoost-enabled hybrid approach is proposed to handle the fatigue causal network. It can make adaptive proactive fatigue predictions to dynamic traffic conditions. Finally, a novel work arrangement algorithm is introduced to arrange a group of operators to a set of work sectors.

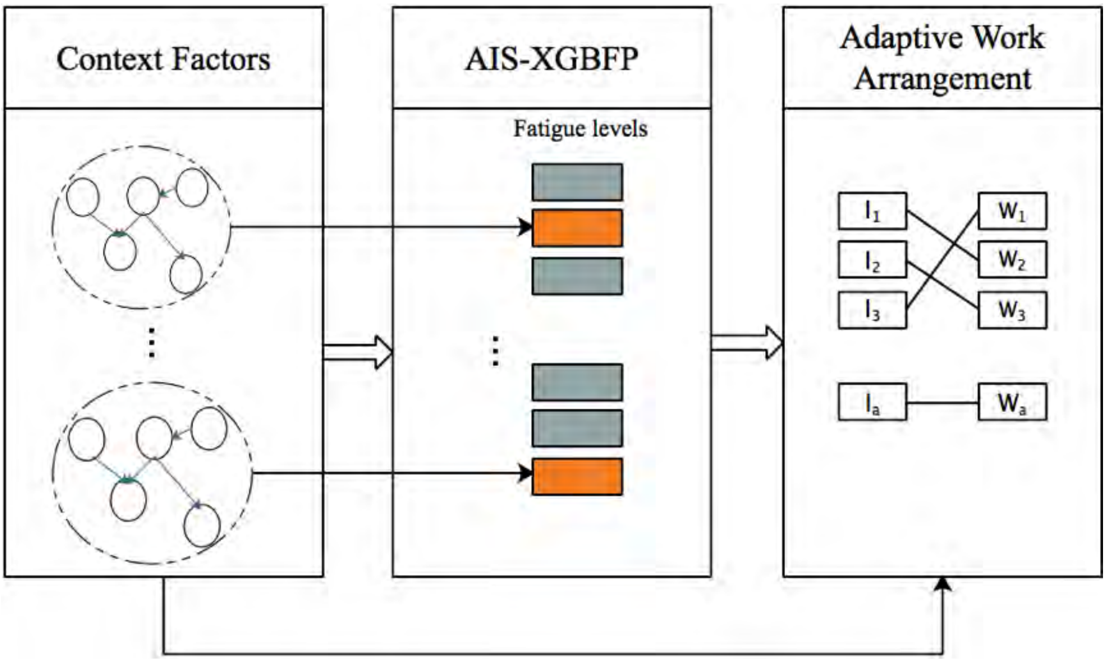

Figure 3. Proposed framework of context-aware fatigue management (I: operator, W: work sector)

4.2 AIS and XGBoost-enabled fatigue prediction

The AIS-XGBFP has three phases, namely AIS-based pre-processing, XGBoost-based training, and predicting. In the first phase, the representative nodes are identified and utilized to simplify the fatigue causal network. The values of the representative nodes are determined by using AIS.

In the second phase, the XGBoost algorithm establishes the fatigue model based on the refined fatigue causal network and corresponding fatigue levels. In the third phase, the fatigue level is predicted by the fatigue model. **Figure 4** depicts the procedures. The details of each stage are summarized below.

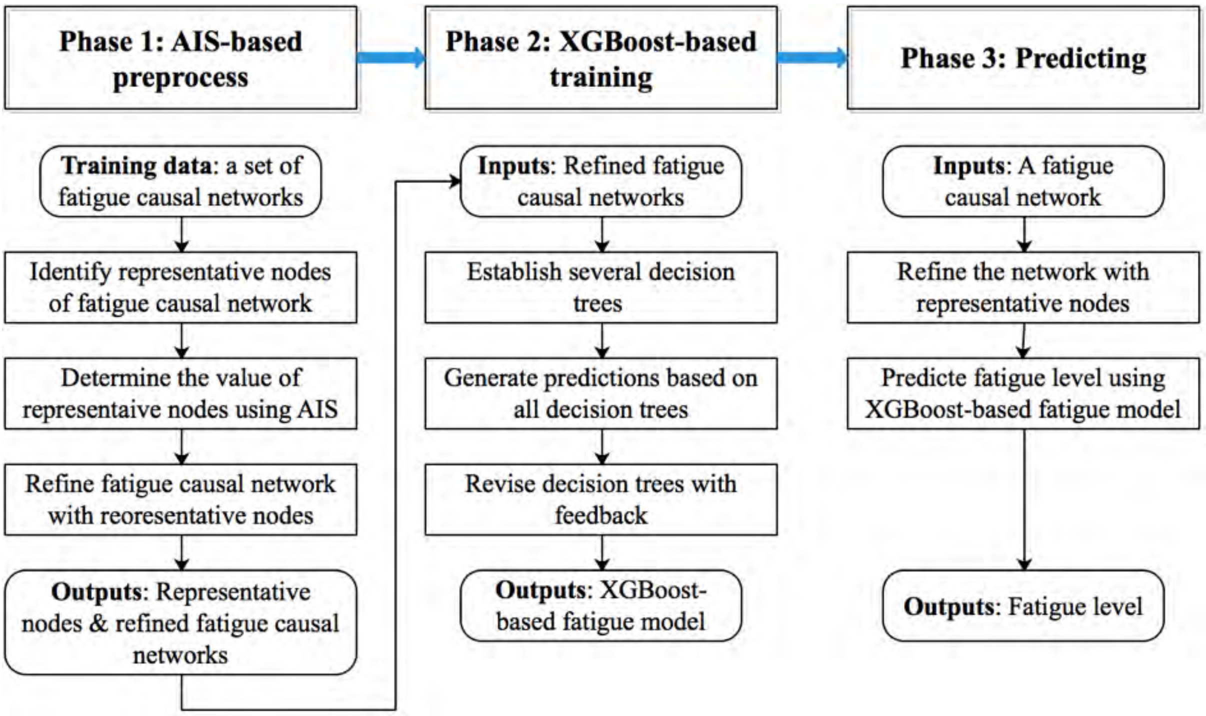

Figure 4. Procedures of the AIS-XGBFP

Phase 1: AIS-based preprocess

In this phase, the raw data is preprocessed to determine the values of representative nodes (*Pn*), named antibodies in AIS. The raw data are cleaned and structured before preprocessing. The first step is to delete noisy data. Specific populations may be less likely to participate in a survey even if invited (e.g. elderly operators). What's more, some participants may be unwilling to answer certain questions (e.g. personality, workload). These challenges can result in incomplete information/missing data during a questionnaire survey. Thus, questionnaires with non-response items are ignored in this research. The second step is normalization. The data collected from the questionnaire include categorical variables and numerical variables.

For categorical variables, they are encoded into a binary vector using a one-hot encoding. For numerical variables, they are normalized first, and further scaled from 0 to 1, so that the value of causal factors ranges from 0 to 1.

The representative nodes are generated based on the fatigue causal network. The causal factors that have inter-relations are grouped into one representative node, named antibody in AIS. The interrelations between any two causal factors can be obtained from Eq (1). The values of the representative nodes are determined according to the training data, named vaccine (Va) in AIS. Each introduced training data is presented to the initial representative nodes. By comparing the Euclidean distance between the training data and the representative nodes, the nodes with the highest similarity to the training data can be identified. Update the value of the representative nodes with the mean values of their neighbor training data until the values are steady.

In this way, the fatigue causal network can be refined by the updated presentative nodes. Since each node represents several causal factors, the fatigue causal network can be simplified.

Phase 2: XGBoost-based training

The refined causal networks with representative nodes are utilized for training the XGBoost algorithm, which is implemented using the Python libraries. The XGBoost algorithm is trained to predict F_i based on training data, $Va = < Pn, F >$. In the training phase, T boosted trees are generated to optimize the following objective functions:

$$\text{obj} = \sum_{i=1}^{I} l(F_i, \widehat{F_i}^{(t)}) + \sum_{t=1}^{T} \Omega(f_t) \tag{2}$$

$$\widehat{F_i} = \sum_{t=1}^{T} f_t(Pn) \tag{3}$$

, where l is the training loss function, and Ω is the regularization term. The logistic loss function is adopted as l in this study. The complexity of the boosted tree is utilized as the regularization term. T is the number of boosted tree and f is the function of the boosted tree.

Phase 3: Testing

A set of causal factors, named antigen (*Ag*) in AIS, is utilized to test the proposed method. The testing phase involves finding a set of representative nodes that have a high affinity with the antigen and then predict the level of human fatigue. The procedures are summarized as follows:

Step 1: For each representative node, computer the affinity between the *Ag* and *Pn*.

Step 2: If the affinity is larger than the predefined threshold α, the *Pn* is selected.

Step 3: Repeat Steps 1 to 2 until all *Pns* are tested.

Step 4: Predict the fatigue level by using *Pns* as the input of the XGBoost algorithm. The fatigue level can be predicted by reassembling the boosted trees (Eq. 3).

4.3 Adaptive work arrangement

An adaptive work arrangement approach is introduced in this sub-section. Following the permutation formula, there are Z! ways to arrange Z operators to Z work sectors. The objective of the adaptive work arrangement is to figure out an optimized work arrangement based on working conditions and individual resilience to mitigate the risk of human fatigue. Hence, the problem can be denoted as below, where

$$min. F_{sum} = \sum_{b=1}^{Z} xgb\{E, W_b, C, I_b\}, \tag{4}$$

$$for\ any\ b\ and\ a \in [1, Z], W_b \neq W_a, I_b \neq I_a$$

$$for\ b \in [1, Z], F_b = xgb\{E, W_b, C, I_b\} < F_{threshold}$$

The fatigue level of every person should not be higher than the threshold. To reduce the complexity of working arrangements, the authors propose to divide work sectors into several groups and then conduct work arrangements. Given two tasks $W_b = \{w_{b1}, w_{b2}, \dots, w_{bR}\}$ and $W_a = \{w_{a1}, w_{a2}, \dots, w_{aR}\}$, R is the number of causal factors belonging to working conditions, their similarity is calculated based on the following Eq (5):

$$S_{ba} = 1 - \sum_{r=1}^{R} (w_{br} - w_{ar}) / R \tag{5}$$

Classify work sectors into the same group if their similarity was higher than a defined threshold α. In this way, the complexity of arranging Z operators can be reduced. AIS-XGBFP is used to predict the fatigue level of each work arrangement, and the work arrangement with the lowest fatigue score will be selected. **Algorithm 1** shows the pseudo-code of the proposed adaptive work arrangement. The concept of Algorithm 1 is rearranging operators to the other work sector where they can keep alert or no change. For example, an operator H working in the Coastal sector is fatigued while H is predicted to be alert in the Port sector. If there is another operator A working in the Coastal sector. A can keep alter or maintain the same state after rearranging to the Port sector. Then operator A and operator H can be switched and well arranged in Port sector and Coastal sector, respectively.

Algorithm 1: Context-aware work arrangement

Inputs: I: the set of workers $\{I_1, \dots, I_Z\}$
W: the set of grouped tasks $\{GW_1, \dots GW_Q\}$

$Size_q$: the number of slots belonging to GW_q
CP: the set of workers whose task should be rearranged
For all $I_z \in I$, $GW_q \in W$
    $F_z = \{F_{z1}, \dots, F_{zq}, \dots, F_{zQ}\}$
    $\Delta_z = maxF_z - minF_z$
    If $\Delta_z > 0$
        $I_z \rightarrow CP$
    end
End
$N_a = 0$
While size (CP)>0
        For all $I_z \in I$, $GW_q \in W$
            $F_z = \{F_{z1}, \dots, F_{zq}, \dots, F_{zQ}\}$
            $\Delta_z = maxF_z - minF_z$
            If $\Delta_z > 0$
                $I_z \rightarrow CP$

end
End
Rank CP from max to min based on Δ
For n=1:1:size (CP)
Find GW_a, where $F_{cp_n a} == minF_{cp_n}$
$N_a = N_a + 1$
If $N_a < Size_a$
Get$\{CP_n, GW_a\}$
Delete CP_n from CP & I
Update CP
Else
Get$\{CP_n, GW_a\}$
Delete CP_n from CP & I
Delete GW_a from W
Update Δ_z
Update CP
End
End
End while

Outputs *{CP, GW}* the recommended work arrangement

5. Case Study

Vessel Traffic Service (VTS) is a shore-side service to guarantee the safe and efficient navigation of vessels in the port and coastal area [45]. During field studies, it has been found that VTS operators (VTSOs) have a high risk of suffering from human fatigue. Hence, local ones are invited to participate in the case study, to validate the effectiveness of the proposed context-aware fatigue management.

The proposed context-aware fatigue management was evaluated from two aspects: the performance of human fatigue prediction (Section 5.2) and the performance of adaptive work arrangement (Section 5.3). This research adopts *accuracy* and *deviation* as performance evaluators. *Accuracy* refers to the proportion of true results, and *deviation* is indicated by the average of the squares of the errors. To evaluate the adaptive work arrangement, the authors compared the fatigue levels of the current work arrangement with the recommended work arrangement. Furthermore, the changes in the work arrangement were described.

Data from local VTS were collected for establishing a fatigue model and described in Section 5.1.

5.1 Fatigue model

The data about human fatigue and causal factors were extracted from a questionnaire-based survey. A total of 132 VTS Operators (VTSOs) from the port authority took part in this survey. Among these VTSOs, 119 of them are males, and the rest are females, with an average working experience of 11 years. The fatigue generation process and sleep quality of sleep disorder patients are different from regular operators. Hence, all participants were initially screened to eliminate those with sleep disorders. All participants were asked to refrain from consuming drugs and coffee before the survey.

The information about individual resilience, working conditions, environment, and circadian rhythm was collected. Following the previous study [16], individual resilience mainly refers to demographical variables, personality factors, and physical conditions. In general, demographical variables include age, gender, nationality, and experience. Personality factors such as extraversion and sensation seeking can be mediating precursors to human fatigue. They can be assessed by using the Bortner type A scale, which is a simple self-report scale [46]. The Bortner type A scale (Appendix A) includes 14 aspects such as extremes of ambition, competitiveness, punctuality, and so on [46]. In this study, physical condition is measured by the so-called Fatigue Severity Scale (FSS) [47]. The FSS (Appendix B) has a 9-item self-report questionnaire scale that contains nine statements, such as motivation and physical functions. The type, intensity, and length of work are critical work-related factors that contribute to human fatigue. The type of VTS operations can be defined based on SOLAS Chapter V, Regulation 12. Primarily, the length of work is indicated by working hours. The intensity of work can be assessed by using the NASA Task Load Index (NASA-TLX) scale [48]. NASA-TLX scale assesses workload from six aspects, namely mental demand, physical demand, temporal demand, performance, effort, and frustration.

The environment is a crucial aspect of VTS operations. More specifically, a dim environment strains the eyes when monitoring the vessels. Moreover, insufficient lighting and warmer core body temperature can promote fatigue [49, 50]. Hence, light and temperature are considered in this case study. Some researchers focused on investigating the effects of circadian rhythm or the impact of time on task. In practice, these two factors induce human fatigue interactively. Thus, time of day, rest after shift, shifts and time on task are studied to indicate the level of the circadian rhythm.

In total, 33 variables were gathered, as shown in **Figure 5**. Based on that, a fatigue causal network (see **Figure 5**) has been constructed. In terms of human fatigue, the 7-point Samn–Perelli Fatigue Scale [51] was adopted to evaluate the subjective fatigue level, where '1' refers to alert, and '7' refers to fatigued. In total, 705 records of human fatigue were collected, ten records of which were discarded due to item nonresponse. The rest fatigue records were utilized for training and testing the proposed method. Each fatigue record includes 33 causal factors and a corresponding subjective human fatigue level.

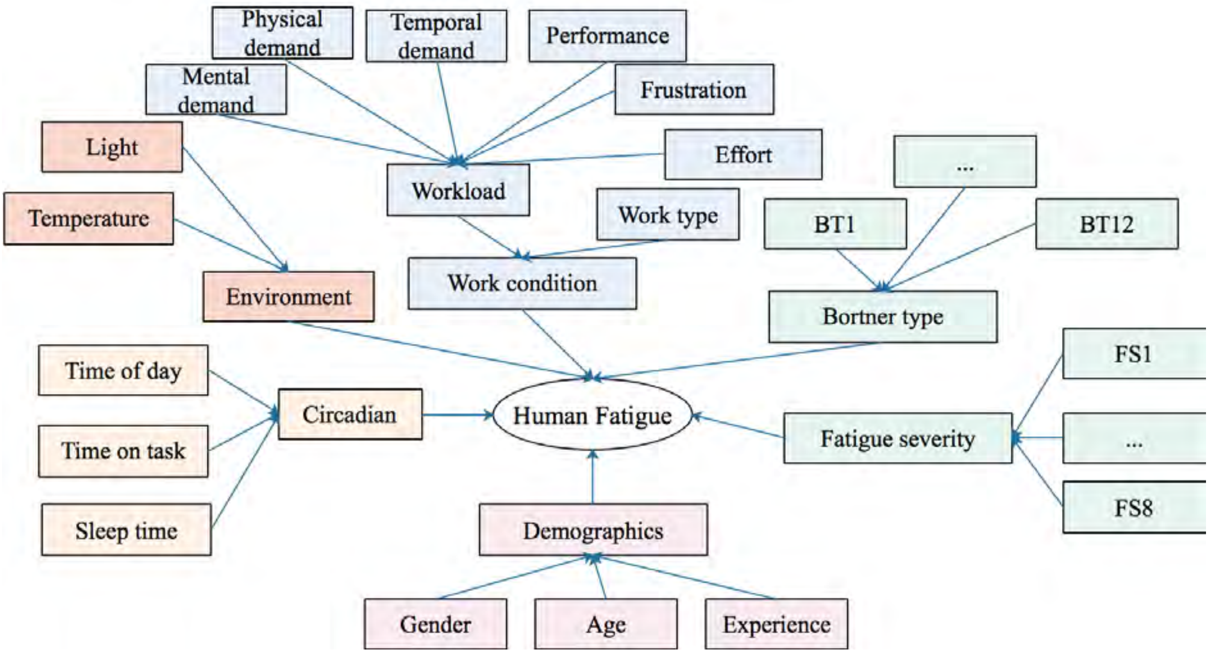

Figure 5. The fatigue causal network of VTS [16] (FS: The elements of fatigue severity (**Appendix A**). BT: The elements of the Bortner type A (**Appendix B**).

5.2 A comparative study of fatigue prediction

In this section, the proposed AIS-XGBFP was compared with those well-known methods, including Decision Tree Regression (DTR), Random Forest Regression (RFR), SVM, and Linear Regression (LR). The parameters of DTR, LR, SVR, and RFR were determined by using the built-in hyperparameter optimization function of Matlab R2018a. The parameters of the AIS-XGBFP were determined as follows.

According to the research study of Lu et al. [52], the affinity threshold should be set as 0.7 and the recognition size threshold should be set as 0.2 to guarantee accuracy and limit the number of the representative nodes. For the other two parameters, we applied a greedy approach to determine their values. In general, the number of boosted trees is set between some hundreds and thousands. The maximum depth of a tree is set to four to six to reduce model complexity. In this study, the number of boosted trees was decided according to the experimental results by setting the value as 500, 1000 and 1500. Similarly, the maximum depth of a tree was decided according to the experimental results by setting the value as 3, 4 and 5. It is found that 1000 boosted trees with a depth of 4 can achieve the best performance. **Appendix C** shows how the performance of the decision tree model varies with the leaf number. The values of four parameters are shown in **Table 1**.

Table 1: Parameters of AIS-XGBFF

Parameters	Value
Affinity threshold **α**	0.7
Recognition pool size threshold β	0.2
The number of boosted trees	1000
The maximum depth	4

Table 2: The results of 10-fold cross validation

Methods	AIS-XGBFP	LR	SVR	DTR	RFR
Accuracy	0.89	0.88	0.82	0.84	0.85
Deviation	0.09	0.26	0.16	0.12	0.10

Table 2 shows the performance of all these methods in predicting human fatigue. The detail results are shown in **Appendix D**. The AIS-XGBFP showed the highest accuracy and lowest deviation.

Analysis of variance (ANOVA) was conducted to test the performance differences between the proposed approach and the other four methods. The statistical analysis was conducted in the SPSS software environment (version 19). A 5% significance level was adopted in all tests. **Table 3** shows a significantly higher accuracy of AIS-XGBFP ($p < 0.05$) compared with the other four methods. Furthermore, compared with SVM and LR, AIS-XGBFP showed a significant lower deviation ($p<0.05$) as well. It is quite clear that the stability and accuracy of the proposed method are significantly better than the other methods.

Table 3: Comparison of prediction performance between AIS-XGBFP and the others

Algorithm	Algorithm	Sig. (Accuracy)	Sig. (deviation)
AIS-XGBFP	DTR	.000	.182
	LR	.001	.003
	RFR	.000	.464
	SVR	.000	.000

5.3 Adaptive work arrangement

In this section, the performance of the adaptive work arrangement was tested by comparing it with the present work arrangement in local VTS. The fatigue levels of the current work arrangement have been collected in Section 5.1. The authors randomly selected 20 sets of historical data from the dataset mentioned in Section 5.1. Each set of data was obtained at the same time, including information of eight operators, their work sectors, environment, and their fatigue levels. In other words, each set of data refers to a current work arrangement and corresponding fatigue levels.

The proposed context-aware fatigue management system was utilized to rearrange each current work arrangement, resulting in the recommended adaptive work arrangement. First, the work sectors of the local VTS were analyzed. There are eight work sectors in local VTS. In other words, eight operators have to work at the same time to provide service to vessels in the designated area. According to SOLAS Chapter V, Regulation 12, there are two types of VTS operations, namely Port and Coastal. Due to the distinction between the Port and Coastal operations, operators performing different operations would suffer from varying levels of workload. Hence, the authors classified the works sectors into two groups, Port operations and Coastal operations. For eight operators, there are 40320 ways to arrange them to eight different work sectors. The result is obtained from the permutation formula A(8, 8)= 8!. After classifying the work sectors into two groups, there are 56 ways to arrange them. The result is obtained from the combination formula C(8, 3) = 8!/(3!*5!). In this way, the complexity of the work arrangement can be reduced. Second, **Algorithm 1** was adopted to provide a recommended work arrangement. Finally, the fatigue level of the approved work arrangement was obtained by AIS-XGBFP. The predicted fatigue level of each operator is “0” or “1”, where “1” means fatigued and “0” means alert.

Figure 6 shows a comparison of the original work arrangement and the recommended work arrangement. The recommend work arrangement can significantly reduce the sum fatigue levels of eight operators. As mentioned, 20 sets of historical data were collected. For each collection of data, the work sectors were rearranged and compared with the current arrangement, resulting in 20 trials.

The changes in work arrangement are presented in **Figure 7**. In this case study, rearranged operators are the ones whose state can be improved by changing their work sectors. On average, the states of 27% operators could be improved by the recommended work arrangement. **Figure 8** presents an example comparing the original work arrangement and the proposed work arrangement. In this example, operator A was predicted to be alert for both port and coastal operations. Operator H was predicted to be fatigued for coastal operation and alert for port operation. Hence, the proposed adaptive work arrangement method suggested to rearrange them. Specifically, operator H was arranged to work in the Port sector, and operator A was arranged to work in the Coastal sector.

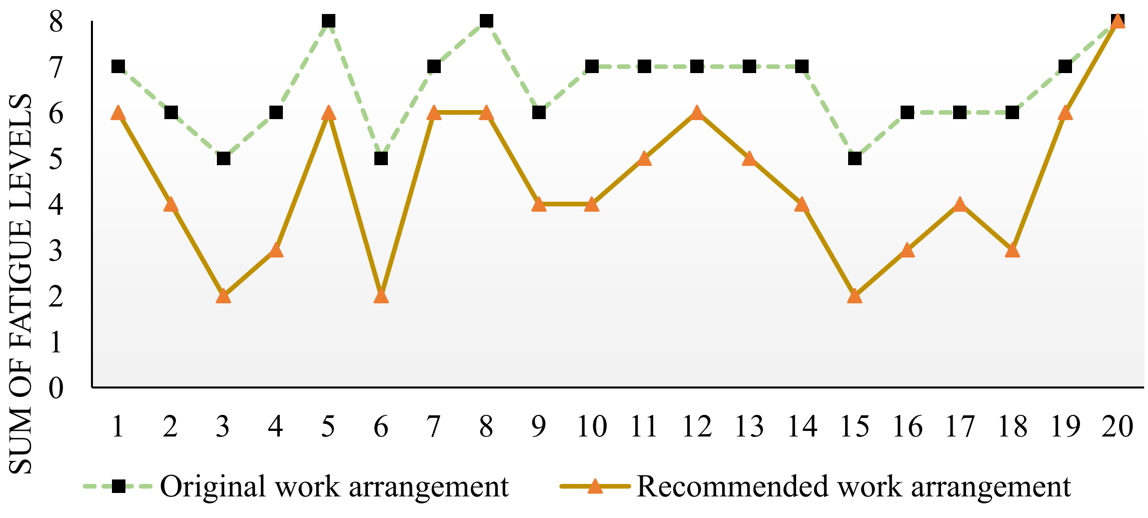

Figure 6. The sum of fatigue levels of eight operations in 20 trials

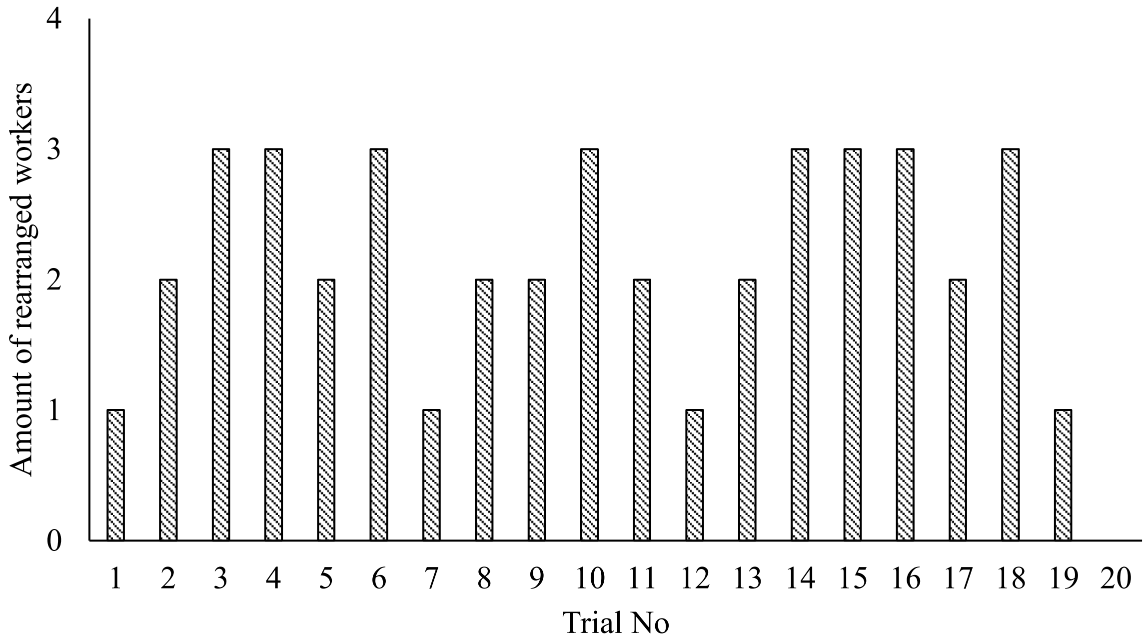

Figure 7. The amount of operators should be arranged in 20 trials

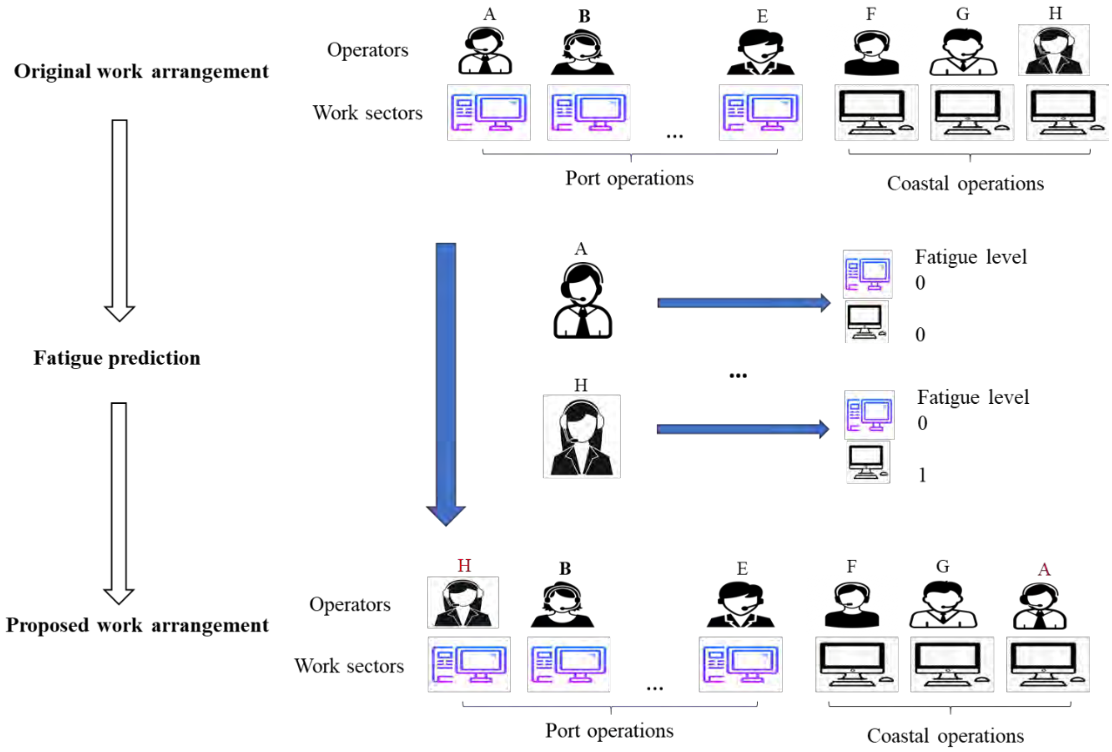

Figure 8. An example comparing the original and the proposed work arrangement

5.4 Discussion

In this section, the data collected from the local vessel traffic service center were analyzed by the proposed method. Owing to the limited data source, the performance of the proposed model may be affected. Specifically, proportionally few females participated in the questionnaire-based survey, resulting in biased data for model training. Hence, for female participants, the trained model may be over-fitting. Nevertheless, the problem can be mitigated by selecting the appropriate affinity threshold. Specifically, the results of the case study show that the model trained by the database can achieve an accuracy of 89%. A comparative study was conducted to compare the performance of the widely used methods, including DTR, RFR, SVM, and LR with the proposed AIS-XGBFP. The AIS-XGBFP showed the highest accuracy and lowest deviation. The statistical tests indicated that the proposed fatigue prediction method could achieve better performance than other typical machine learning methods. Besides, it was found that there existed substantial individual differences in the susceptibility to become fatigued, which revealed the necessities of a promising adaptive work arrangement. The case study in local VTS indicated that the adaptive work arrangement improve the states of 27% operators. By considering individual differences and work types, the novel scheduling algorithm can provide adaptive work arrangement to lower the occurrence of fatigue. However, most of the operators still suffer from a high possibility of human fatigue with the proposed work arrangement. Specifically, Figure 6 shows that only 6 out of 20 trials, where fewer than 50% of operators are fatigue. Hence, fatigue is still a critical problem in VTS. According to the field observation and expert interview, monitoring vessel movements for is monotones and quickly induce human fatigue. Adaptive work arrangements can reduce monotones. However, the problem of monitoring is still existing.

6. Conclusion

In this study, a context-aware fatigue management approach was proposed to mitigate the risks of human fatigue in traffic control operators. It consists of two main modules, namely AIS and XGBoost-enabled fatigue prediction, and adaptive work arrangement. Experiment results obtained from the case study demonstrated the validity of the two modules. The main contributions of this research can be summarized as follows:

1) *A systematic approach to context-aware human fatigue management in traffic control centers*. In general, this work provides a thorough study from representing context factors of human fatigue to rearrange work sectors and serves as a foundation of context-aware fatigue management in traffic management authorities. Since human fatigue is a common phenomenon in various work settings, this approach could be extended and utilized in these work settings to reduce the risks of human fatigue.

2) *The fatigue casual causal network which allows systematically representing various factors and the inherent uncertainties associated with these factors was proposed*. Based on this, a novel fatigue prediction algorithm was developed to consider the contextual factors of human fatigue seriously. This module provides a theoretical foundation for scheduling individual working time.

3) *An adaptive work arrangement algorithm was proposed to redesign work schedules to reduce the risks of human fatigue*. By considering individual differences and work types, the scheduling algorithm can provide adaptive work arrangements with lower fatigue occurrence.

Despite their effectiveness of the context-aware fatigue management, some limitations of this study still exist. It is expected that a proportion of the working population would have a sleep disorder. Nevertheless, sleep disorder operators were not considered in this study. This limitation affects the usability of the model in practice. For example, the causal factors were collected through questionnaires, subjected from time delay. In the future, context-aware fatigue management can take advantage of the current information technologies (e.g. Internet-of-Things) to efficiently collect contextual information. Meanwhile, the proposed method can be implemented in other control room environment, such as the nuclear power industry, automation control center via deeply investigating the specific causal factors. Moreover, future works can investigate some interventions to reduce monotones caused by monitoring. It is hoped that this study can contribute to the understanding and implementation of context-aware management in the human fatigue field of research and provide insightful guidance to the traffic management authorities.

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Reference

1. Metzger, U. and R. Parasuraman, *The role of the air traffic controller in future air traffic management: An empirical study of active control versus passive monitoring.* Human Factors, 2001. **43**(4): p. 519-528.
2. Härmä, M., et al., *The effect of an irregular shift system on sleepiness at work in train drivers and railway traffic controllers.* Journal of sleep research, 2002. **11**(2): p. 141-151.
3. Jones, C.B., et al., *Working hours regulations and fatigue in transportation: A comparative analysis.* Safety science, 2005. **43**(4): p. 225-252.
4. Akhtar, M.J. and I.B. Utne, *Human fatigue's effect on the risk of maritime groundings–A Bayesian Network modeling approach.* Safety science, 2014. **62**: p. 427-440.
5. Alonso, F., et al., *Prevalence of physical and mental fatigue symptoms on Spanish drivers and its incidence on driving safety.* Advances in psychology neuroscience, 2016. **1**(2): p. 10-18.
6. Li, F., et al., *Hybrid data-driven vigilance model in traffic control center using eye-tracking data and context data.* Advanced Engineering Informatics, 2019. **42**: p. 100940.
7. Ji, Q., P. Lan, and C. Looney, *A probabilistic framework for modeling and real-time monitoring human fatigue.* IEEE Transactions on systems, man, and cybernetics-Part A: Systems and humans, 2006. **36**(5): p. 862-875.
8. Moore-Ede, M., et al., *Circadian alertness simulator for fatigue risk assessment in transportation: application to reduce frequency and severity of truck accidents.* Aviation, space, and environmental medicine, 2004. **75**(3): p. A107-A118.
9. Dawson, D., D. Darwent, and G.D. Roach, *How should a bio-mathematical model be used within a fatigue risk management system to determine whether or not a working time arrangement is safe?* Accident Analysis & Prevention, 2017. **99**: p. 469-473.
10. Parkes, K.R., *Shift schedules on North Sea oil/gas installations: a systematic review of their impact on performance, safety and health.* Safety science, 2012. **50**(7): p. 1636-1651.
11. Gander, P., *Fatigue management in air traffic control: the New Zealand approach.* Transportation research part F: traffic psychology and behaviour, 2001. **4**(1): p. 49-62.

12. Thiffault, P. and J. Bergeron, *Fatigue and individual differences in monotonous simulated driving.* Personality and individual differences, 2003. **34**(1): p. 159-176.
13. Strahan, C., B. Watson, and A. Lennonb, *Can organisational safety climate and occupational stress predict work-related driver fatigue?* Transportation research part F: traffic psychology and behaviour, 2008. **11**(6): p. 418-426.
14. Winwood, P.C., A.H. Winefield, and K. Lushington, *Work-related fatigue and recovery: the contribution of age, domestic responsibilities and shiftwork.* Journal of Advanced Nursing, 2006. **56**(4): p. 438-449.
15. Phillips, R.O., *A review of definitions of fatigue–And a step towards a whole definition.* Transportation research part F: traffic psychology and behaviour, 2015. **29**: p. 48-56.
16. Li, F., et al. *Contextual information-based human fatigue prediction for integrated traffic control*. in *Proceedings of International Conference on Computers and Industrial Engineering, CIE*. 2018.
17. Borbély, A.A., *A two process model of sleep regulation.* Human neurobiology, 1982.
18. Caldwell, J.A., et al., *Fatigue and its management in the workplace.* Neuroscience & Biobehavioral Reviews, 2018.
19. Belyavin, A.J. and M.B. Spencer, *Modeling performance and alertness: the QinetiQ approach.* Aviation, space, and environmental medicine, 2004. **75**(3): p. A93-A103.
20. Dawson, D., et al., *Modelling fatigue and the use of fatigue models in work settings.* Accident Analysis & Prevention, 2011. **43**(2): p. 549-564.
21. Roach, G.D., A. Fletcher, and D. DAWsON, *A model to predict work-related fatigue based on hours of work.* Aviation, space, and environmental medicine, 2004. **75**(3): p. A61-A69.
22. Bal, E., O. Arslan, and L.J.S.s. Tavacioglu, *Prioritization of the causal factors of fatigue in seafarers and measurement of fatigue with the application of the Lactate Test.* Safety science, 2015. **72**: p. 46-54.
23. Darwent, D., et al., *Managing fatigue: It really is about sleep.* Accident Analysis & Prevention, 2015. **82**: p. 20-26.
24. Hong, J.-y., E.-h. Suh, and S.-J. Kim, *Context-aware systems: A literature review and classification.* Expert Systems with applications, 2009. **36**(4): p. 8509-8522.
25. Zheng, P., et al., *A systematic design approach for service innovation of smart product-service systems.* Journal of Cleaner Production, 2018. **201**: p. 657-667.
26. Braunhofer, M., et al., *Context-aware points of interest suggestion with dynamic weather data management*, in *Information and communication technologies in tourism 2014*. 2013, Springer. p. 87-100.
27. Zheng, P., X. Xu, and C.-H. Chen, *A data-driven cyber-physical approach for personalised smart, connected product co-development in a cloud-based environment.* Journal of Intelligent Manufacturing, 2018: p. 1-16.
28. Zheng, P., et al., *Smart, connected open architecture product: an IT-driven co-creation paradigm with lifecycle personalization concerns.* International Journal of Production Research, 2018: p. 1-14.
29. Jitwasinkul, B., B.H. Hadikusumo, and A.Q. Memon, *A Bayesian Belief Network model of organizational factors for improving safe work behaviors in Thai construction industry.* Safety science, 2016. **82**: p. 264-273.
30. Chang, H.-w., Y.-c. Tai, and J.Y.-j. Hsu, *Context-aware taxi demand hotspots prediction.* International Journal of Business Intelligence and Data Mining, 2010. **5**(1): p. 3.
31. Ravi, N., et al. *Context-aware battery management for mobile phones*. in *Pervasive Computing and Communications, 2008. PerCom 2008. Sixth Annual IEEE International Conference on*. 2008. IEEE.

32. Shen, K.-Q., et al., *A feature selection method for multilevel mental fatigue EEG classification.* IEEE transactions on biomedical engineering, 2007. **54**(7): p. 1231-1237.
33. Kim, Y., Y. Kim, and M. Hahn. *Detecting driver fatigue based on the driver's response pattern and the front view environment of an automobile*. in *2008 Second International Symposium on Universal Communication*. 2008. IEEE.
34. Parhizi, S., L.M. Steege, and K.S. Pasupathy, *Mining the relationships between psychosocial factors and fatigue dimensions among registered nurses.* International Journal of Industrial Ergonomics, 2013. **43**(1): p. 82-90.
35. Kamalian, R., et al. *Reducing human fatigue in interactive evolutionary computation through fuzzy systems and machine learning systems*. in *2006 IEEE International Conference on Fuzzy Systems*. 2006. IEEE.
36. Tango, F. and M. Botta, *Real-time detection system of driver distraction using machine learning.* IEEE Transactions on Intelligent Transportation Systems, 2013. **14**(2): p. 894-905.
37. Shen, K.-Q., et al., *EEG-based mental fatigue measurement using multi-class support vector machines with confidence estimate.* Clinical Neurophysiology, 2008. **119**(7): p. 1524-1533.
38. Chong, Y.T. and C.-H. Chen, *Management and forecast of dynamic customer needs: An artificial immune and neural system approach.* Advanced Engineering Informatics, 2010. **24**(1): p. 96-106.
39. Chen, M.-H., C.-H. Teng, and P.-C. Chang, *Applying artificial immune systems to collaborative filtering for movie recommendation.* Advanced Engineering Informatics, 2015. **29**(4): p. 830-839.
40. Chen, T. and C. Guestrin. *Xgboost: A scalable tree boosting system*. in *Proceedings of the 22nd acm sigkdd international conference on knowledge discovery and data mining*. 2016. ACM.
41. Song, R., et al. *eXtreme gradient boosting for identifying individual users across different digital devices*. in *International Conference on Web-Age Information Management*. 2016. Springer.
42. Grandjean, E., *Fatigue: its physiological and psychological significance.* Ergonomics, 1968. **11**(5): p. 427-436.
43. Grech, M.R., et al., *An examination of the relationship between workload and fatigue within and across consecutive days of work: Is the relationship static or dynamic?* Journal of occupational health psychology, 2009. **14**(3): p. 231.
44. Hollnagel, E., *Cognitive reliability and error analysis method (CREAM)*. 1998: Elsevier.
45. Li, F., C.-H. Chen, and L.P. Khoo, *Information Requirements for Vessel Traffic Service Operations.* World Academy of Science, Engineering and Technology, International Journal of Computer, Electrical, Automation, Control and Information Engineering, 2016. **10**(5): p. 881-885.
46. Shakouri, M., F. Aghazadeh, and L.H. Ikuma, *Individual differences in drivers' perceived workload near construction work zones.* Occupational Ergonomics, 2016. **13**(2): p. 101-117.
47. Krupp, L.B., et al., *The fatigue severity scale: application to patients with multiple sclerosis and systemic lupus erythematosus.* Archives of neurology, 1989. **46**(10): p. 1121-1123.
48. Hart, S.G. and L.E. Staveland, *Development of NASA-TLX (Task Load Index): Results of empirical and theoretical research*, in *Advances in psychology*. 1988, Elsevier. p. 139-183.

49. Fronczek, R., et al., *Manipulation of core body and skin temperature improves vigilance and maintenance of wakefulness in narcolepsy.* Sleep, 2008. **31**(2): p. 233-240.
50. Hursh, S.R., et al., *Fatigue models for applied research in warfighting.* Aviation, space, and environmental medicine, 2004. **75**(3): p. A44-A53.
51. Samn, S.W. and L.P. Perelli, *Estimating aircrew fatigue: a technique with application to airlift operations*. 1982, School of Aerospace Medicine Brooks Afb tx.
52. Lu, X.-Y., et al., *Artificial immune network with feature selection for bank term deposit recommendation.* Journal of Intelligent Information Systems, 2016. **47**(2): p. 267-285.

Appendix

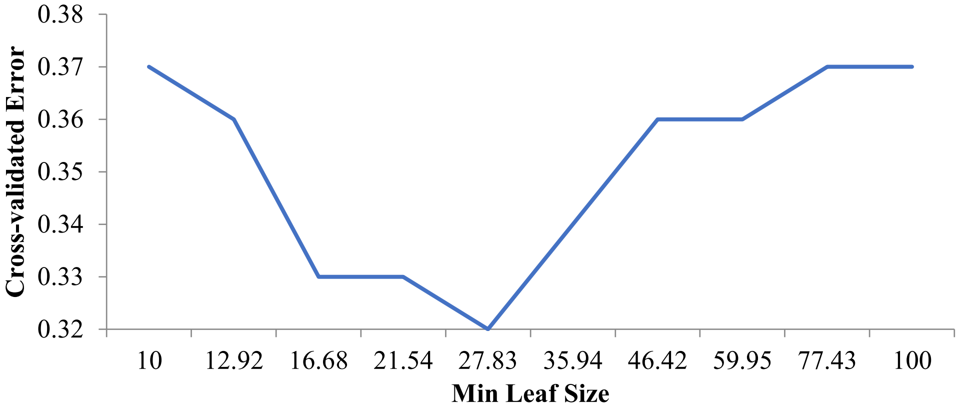
Appendix A：Fatigue severity scale

Items	Descriptions
FS 1	My motivation is lower when I am fatigued.
FS 2	Exercise brings on my fatigue.
FS 3	I am easily fatigued.
FS 4	Fatigue interferes with my physical functioning.
FS 5	Fatigue causes frequent problems for me.
FS 6	My fatigue prevents sustained physical functioning.
FS 7	Fatigue interferes with carrying out certain duties and responsibilities.
FS 8	Fatigue is among my most disabling symptoms.
FS 9	Fatigue interferes with my work, family, or social life.

Appendix B: The Bortner type A scale

Item	Descriptions	Scale							Descriptions
BT1	Never Late	1	2	3	4	5	6	7	Causal about appointments
BT2	Not competitive	1	2	3	4	5	6	7	Very competitive
BT3	Anticipates what others are going to say	1	2	3	4	5	6	7	Good listener, hears others out
BT4	Always rushed	1	2	3	4	5	6	7	Never feels rushed, even under pressure
BT5	Can wait patiently	1	2	3	4	5	6	7	Impatient when waiting
BT6	Goes "all out"	1	2	3	4	5	6	7	Causal
BT7	Takes things one at a time	1	2	3	4	5	6	7	Tries to do many things at once
BT8	Emphatic in speech	1	2	3	4	5	6	7	Slow, deliberate talker
BT9	Wants good job recognized by other	1	2	3	4	5	6	7	Only cares about satisfying himself no matter what others may think
BT10	Fast	1	2	3	4	5	6	7	Slow doing things
BT11	Easy going	1	2	3	4	5	6	7	Hard driving
BT12	'Sits' on feelings	1	2	3	4	5	6	7	Expresses feelings
BT13	Many interests	1	2	3	4	5	6	7	Few interests outside work
BT14	Satisfied with job	1	2	3	4	5	6	7	Ambitious

Appendix C: Performance of decision tree in fatigue prediction vs min leaf size



Appendix D: The 10-fold cross validation results of testing data for each algorithm (Accuracy)

Data source	Algorithm	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	Trial 6	Trial 7	Trial 8	Trial 9	Trial 10	Ave.
All	LR	0.86	0.92	0.88	0.88	0.86	0.88	0.87	0.93	0.81	0.89	0.88
	SVR	0.83	0.81	0.81	0.81	0.84	0.85	0.84	0.77	0.81	0.85	0.82
	DTR	0.77	0.83	0.88	0.81	0.83	0.88	0.86	0.83	0.88	0.81	0.84
	RFR	0.80	0.84	0.88	0.81	0.82	0.88	0.86	0.87	0.88	0.81	0.85
	AIS-XGBFP	0.90	0.88	0.91	0.92	0.86	0.92	0.93	0.86	0.86	0.91	0.89
No PI	LR	0.66	0.79	0.75	0.76	0.79	0.78	0.78	0.64	0.79	0.74	0.75
	SVR	0.72	0.74	0.75	0.75	0.71	0.73	0.71	0.66	0.72	0.69	0.72
	DTR	0.73	0.73	0.71	0.73	0.76	0.76	0.76	0.69	0.72	0.75	0.73
	RFR	0.76	0.73	0.67	0.75	0.74	0.72	0.78	0.77	0.72	0.80	0.74
	AIS-XGBFP	0.85	0.85	0.82	0.81	0.83	0.79	0.78	0.81	0.75	0.85	0.81
No DI	LR	0.85	0.88	0.86	0.86	0.88	0.90	0.86	0.87	0.86	0.90	0.87
	SVR	0.81	0.79	0.79	0.75	0.79	0.77	0.80	0.77	0.80	0.82	0.79
	DTR	0.85	0.79	0.85	0.79	0.82	0.81	0.79	0.83	0.81	0.84	0.82
	RFR	0.79	0.83	0.81	0.85	0.79	0.86	0.83	0.82	0.81	0.81	0.82
	AIS-XGBFP	0.86	0.88	0.88	0.91	0.83	0.89	0.84	0.88	0.89	0.87	0.87
No WC	LR	0.88	0.80	0.86	0.87	0.86	0.84	0.84	0.83	0.83	0.81	0.84
	SVR	0.70	0.75	0.78	0.76	0.75	0.73	0.73	0.72	0.74	0.71	0.74
	DTR	0.85	0.89	0.86	0.82	0.83	0.81	0.80	0.81	0.83	0.83	0.83
	RFR	0.85	0.84	0.83	0.88	0.87	0.83	0.83	0.82	0.80	0.87	0.84
	AIS-XGBFP	0.89	0.82	0.82	0.88	0.88	0.85	0.81	0.82	0.86	0.83	0.85

10