Research on the Reliability of High-Speed Railway Dispatching and Commanding Personnel with Multi Physiological Signals

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Abstract. In the event of equipment failure, traffic accident, natural disaster and other abnormal situations, the timely emergency disposal of the traffic dispatcher is required. In order to accurately evaluate the human reliability of the high-speed railway traffic dispatcher in emergency scenarios, this paper proposes a reliability analysis method based on the Phoenix model. In order to eliminate the dependence of the traditional human reliability analysis method on expert experience, a quantification method based on multiple physiological signals is designed. This paper also gives a specific application of this method in the case of inbound signal machine failure. With this human reliability analysis method, the human reliability of the traffic dispatcher and the causative behavior with the highest probability of failure can be accurately calculated, which can provide a reference for the improvement of the emergency handling protocol.

Keywords: Traffic dispatcher · Human reliability analysis · Physiological signals.

1 Introduction

In the past decades, a variety of Human reliability analysis (HRA) models and methods have been proposed, and the development of HRA can be divided into 3 phases in chronological order [1]. Some classical methods, such as THERP (Technique for Human Error Rate Prediction) and CREAM (Cognitive Reliability and Error Analysis Method) have been widely used in nuclear power [2, 3], mining [4] aviation [5], offshore oil and gas industry [6] and marine transportation [7]. However, in the railway field, there is a general lack of human-caused data in HRA for traffic scheduling and command, which is manifested in the following points:

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first, the data are extremely difficult to collect, leading to difficulties in model quantification; second, data citability, data from other countries or data from other fields, due to differences in cultural background, social environment and nature of operations and other factors, leading to different human behaviors and habits of thinking, making human-caused data inappropriate to refer to; Third, data reliability, the existing HRA is extremely dependent on expert judgment and subjective opinions of method users, which makes the consistency and accuracy of analysis results poor [8]. Therefore, this paper designs a quantification method for human factors data by selecting physiological signals as objective data for HRA, and establishes an HRA model applicable to railway dispatching command based on PHOENIX.

2 PHOENIX-based Human Reliability Analysis Model

The Phoenix method is a HRA model proposed by Ekanem [9], which mixes various methods such as event trees, fault trees, and Bayesian networks. Its framework is divided into 3 layers, as shown in Fig. 1.

(1) The top layer is the Human Fault Event Layer (HFE), an event tree model, which aims to identify the HFE and analyze the tasks to be solved by operators in a chronological order to find the risk points that may lead to task failure, which have two states of success/failure and whose probability values of occurrence of the two states are calculated by the middle layer fault tree.

(2) The intermediate layer is the Crew Failure Model layer (CFM), which is a fault tree model, and this layer aims to analyze the HFE retrospectively and per-form deductive reasoning on. Combining the IDAC and SRK models, the cognitive behavior of the dispatcher is divided into: information perception I, rule based diagnostic decision D-1, knowledge-based diagnostic decision D-2, and action execution A, and all failure modes are identified to constitute the CFM set.

(3) The bottom layer is the Performance Shaping Factor layer (PSF), which is a Bayesian network model, mainly reasoning about the probability of occurrence of failure modes, and quantifying and analyzing the occurrence probability of CFM by constructing a causal logic model between PSFs.

3 Human factors data quantification methods based on physiological signals

3.1 Quantifiable Human Factors Data Collection

Subjects. Data for this experiment were obtained from 20 graduate students, 14 males and 6 females, aged between 22 and 26 years. The subjects were of normal mind, normal or corrected hearing and vision, and had the necessary basic train operation control knowledge. A week-long training was given to them before participating in the experiment, and the training content was the disposal process

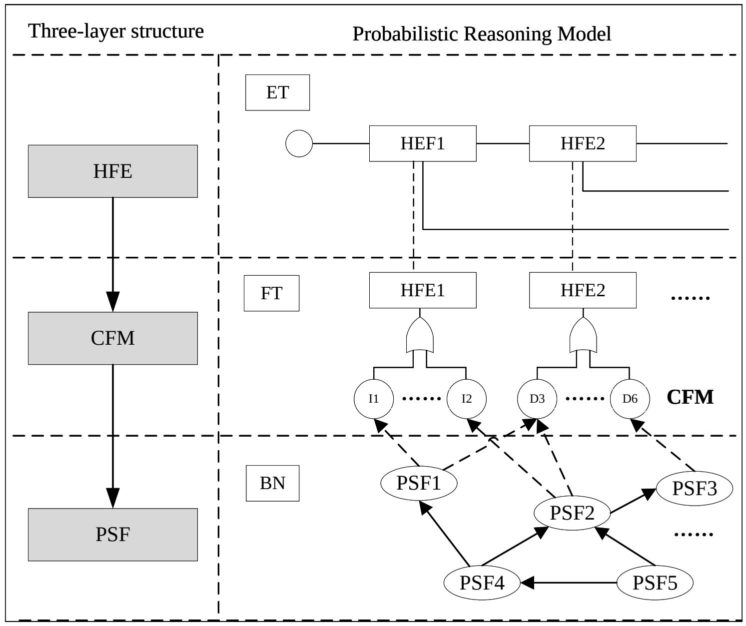

Fig. 1. Model Structure.

summarized by the standard dispatching command process for six emergency scenarios.

Experimental protocol. Stress, attention and workload from the PSF library were selected as quantitative human factors data to design high, medium and low level evoked experiments and dispatching command experiments and to collect Electroencephalogram(EEG), Photoplethysmographic(PPG) and Electrodermal activity(EDA). The stress-induced experiments used a mental arithmetic task, the attention-induced experiments used a game task, and the workload induced experiments used CPT and N-back dual tasks; the dispatching experiments included high wind alarm, incoming signal machine failure, foreign object intrusion limit, automatic train lowering bow, loss of turnout indication and signal closure in open state. Each group of experiments contains three evoked experiments and six dispatching command emergency scenarios, all conducted on the human factors engineering experimental platform shown in Fig. 2.

3.2 Feature Engineering

Preprocessing. Wavelet thresholding is applied to EEG, PPG and EDA for noise reduction, and ICA is used to remove the EOG component of EEG to obtain high-quality physiological signals.

Fig. 2. Experimental platform.

Feature extraction.Through data. processing, time domain, frequency domain and nonlinear features are extracted to obtain 224 EEG features of 14 types in 16 channels, 11 PPG features and 8 EDA features.

Feature selection. The RF-SFFS(Random Forest - Sequential Floating Forward Selection) feature selection algorithm constructed in this paper firstly constructs an existing feature subset using the feature importance of RF; then performs SFFS search and uses the classification accuracy of RF as the discriminant criterion of SFFS, traverses the unselected features, and if adding the feature to the feature subset makes the RF classification accuracy higher, then adds the feature to the subset; traverses the selected features, and if adding the If the feature is removed to increase the classification accuracy, the feature is removed, and the search stops when the preset number of features is finally reached, and the optimal feature subsets are obtained as follows: 3 PPG features for pressure level classification, 24 EEG features for attention level classification, and 18 multi-modal features for workload level classification.

Table 1. Classification results.

Status	Classifier	Accuracy(%)	Precision(%)	Recall(%)	F1(%)
Pressure	KNN	60.8	59.6	61.2	60.4
	SVM	65.3	59.8	65.6	62.6
	XGBoost	76.8	77.4	77.1	77.2
Attention	KNN	66.1	66.3	65.9	66.1
	SVM	71.6	73.2	72.3	72.7
	XGBoost	81.2	81.7	81.6	81.6
Workload	KNN	58.4	66.3	65.9	58.7
	SVM	65.5	73.2	72.3	66.7
	XGBoost	79.6	81.7	81.6	79.9

3.3 Status level classification

In this paper, three algorithms, KNN, SVM and XGBoost, were selected for multi-level level identification of attention, stress and workload, and the classification model with high accuracy was selected to be applied to state identification and prior probability assignment for scheduling experiments. The identification results are shown in Table 1, and it was found that XGBoost performed better than the first two, and the accuracy rates in the three classifications of stress, attention and workload were 76.8%, 81.2% and 79.6%, respectively, so XGBoost was chosen as the classifier for human factors data quantification.

4 Example analysis

4.1 Qualitative analysis

HFE layer. Selecting the home signal failure under the CTCS-3 train control system as the travel scenario, the event tree model shown in Fig. 3

CFM layer. CFM classification of the 14 behaviors in the figure, with the failure behavior as the top event and the failure mode as the bottom event to construct the fault tree model. The CFM classification is shown in the fig.. 4.

PSF layer. Combined with the trained XGBoost model can identify the stress level, attention level and workload of dispatchers in emergency disposal, by counting the present probability of the high and low levels of the three as the prior probability of Bayesian network nodes, accordingly all parent nodes of the three can be eliminated as shown in Fig. 5.

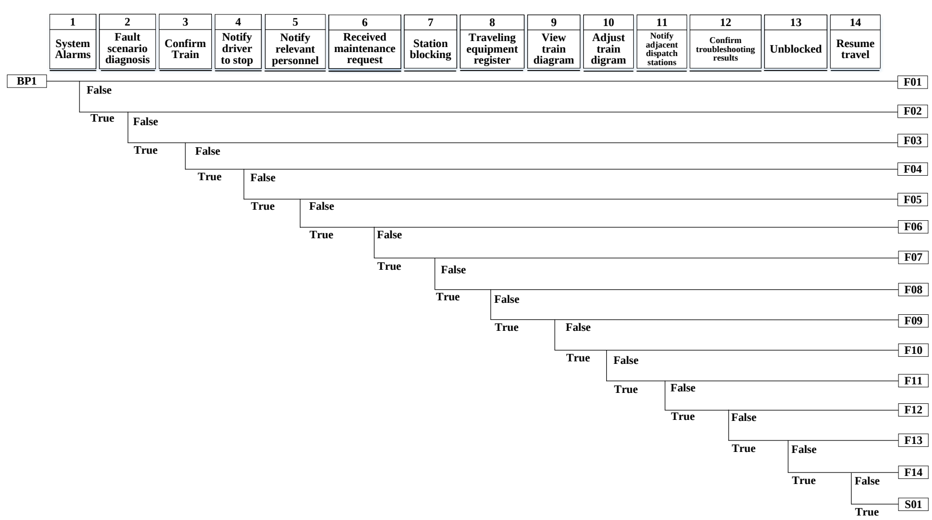

Fig. 3. Event Tree Model.

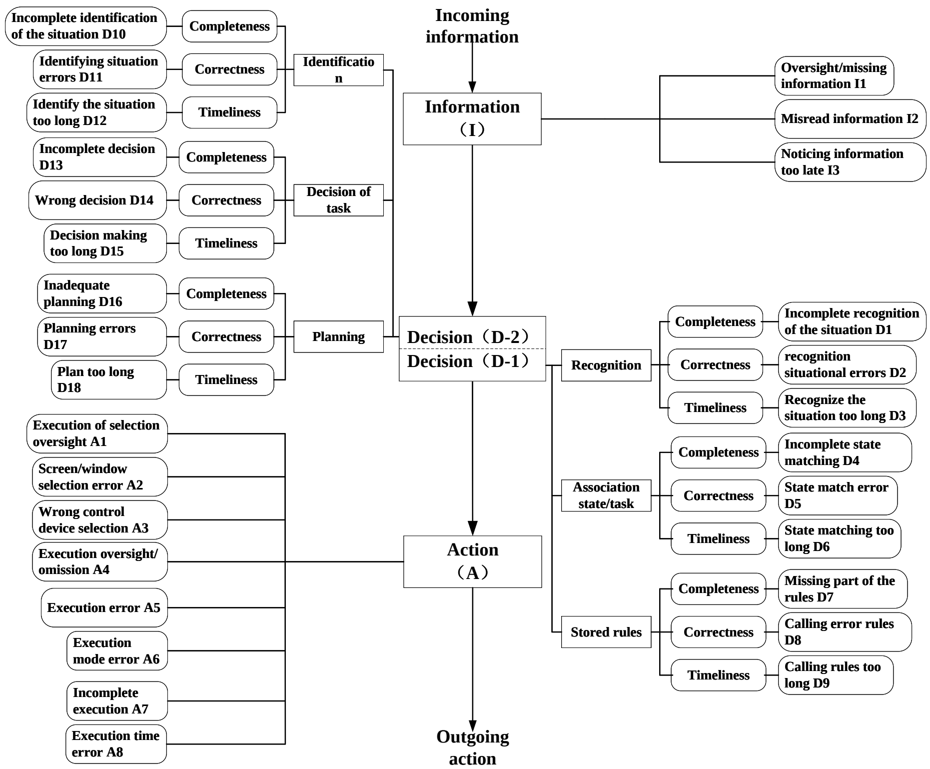

Fig. 4. CFM classification.

4.2 Quantitative analysis

(1) BN inference. Prior probability assignment, for unmeasurable nodes using D-S evidence theory to fuse the judgment results of different experts, for measurable nodes using XGBoost recognition statistics of high and low levels of present probability as the prior probability of Bayesian network nodes; conditional probability assignment is achieved by fuzzy inference algorithm [10]; the Bayesian network inference results of four cognitive stages are obtained.

(2) CFM occurrence probability calculation. Through the SLIM-BN algorithm [11], the Bayesian network root nodes are all placed in the best and worst states to obtain two SLIs and solve for the values of the unknowns a and b as shown in Eq.2. Then, the BN inference results in the original state are substituted into Eq.1 to calculate the probability of CFM occurrence as shown in Table 2.

$$\begin{cases} \lg HEP_{\min} = aSLI_1 + b \\ \lg HEP_{\max} = aSLI_2 + b \end{cases} \tag{1}$$

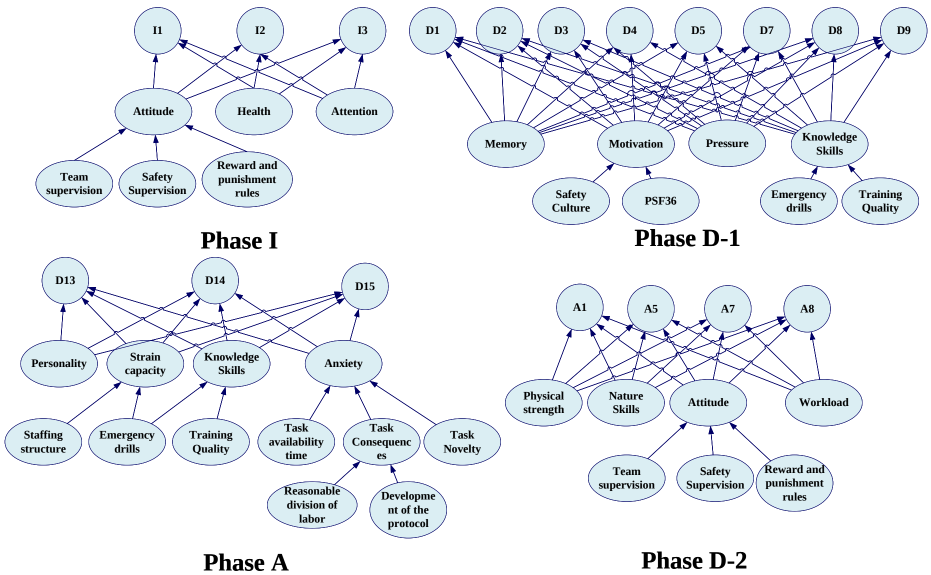

Fig. 5. Bayesian network structure at different phases.

$$\lg HEP = aSLI + b \tag{2}$$

Table 2. CFM occurrence probability.

Phase I	probability	Phase D-1	probability	Phase D-2	probability	Phase A	probability
I1	2.420e-04	D1	8.962e-05	D13	2.982e-02	A1	3.401e-04
I2	2.038e-04	D2	7.598e-05	D14	2.326e-02	A5	4.634e-04
I3	1.903e-04	D3	1.098e-04	D15	2.557e-02	A7	4.184e-04
		D4	8.360e-03			A8	1.851e-04
		D5	6.946e-03				
		D7	1.462e-03				
		D8	2.487e-03				
		D9	8.089e-03				

(3) Event tree inference. The probability of occurrence of various CFM is obtained, so that the cognitive behaviors decomposed in the HEF layer can be mapped with CFM as shown in Table 3. Since the task is a tandem task, all behaviors must succeed in order for the task to succeed, so the human reliability of the home signal fault scenario is 0.93265 by event tree inference as shown in Equation 3, and the causative actions with the highest probability of failure

are fault diagnosis, confirming the results of troubleshooting, and registering the traveling equipment register.

Table 3. CFM occurrence probability.

Behavior number	Possible CFM	Failure probability	Success Probability	Corrected Probability
1	I1\I2\I3	6.3610e-04	0.99936	0.99936
2	D13\D14\D15	0.07865	0.92135	0.96067
3	D1\D2\D3	2.7540e-04	0.99972	0.99976
4	A1\A5\A8	9.8860e-04	0.99901	0.99950
5	A1\A5\A7\A8	0.00141	0.99859	0.99866
6	I1\I2\I3	6.3610e-04	0.99936	0.99936
7	A1\A5	8.0350e-04	0.99920	0.99960
8	D7\D8	0.00395	0.99605	0.99625
9	I2	2.0380e-04	0.99980	0.99981
10	D7\D8\D9	0.01204	0.98796	0.99398
11	A1\A5\A8	9.8860e-04	0.99901	0.99950
12	D4\D5	0.01531	0.98469	0.98546
13	A1\A5	8.0350e-04	0.99920	0.99960
14	A1\A8	5.2520e-04	0.99947	0.99974

$$P(S) = P(HFE1) \times P(HFE2) \times \cdots \times P(HFE14) = 0.93265 \qquad (3)$$

5 Conclusion

In this paper, a PHOENIX model-based HRA method is proposed to realize the macro level of dispatcher's error behavior, gradually refine to the possible CFM, and then obtain the influential PSF, and reduce the component of expert judgment in model quantification to make the analysis results objective. The design of a human factors data quantification method based on physiological signals achieves hierarchical identification of stress, attention and workload with average accuracies of 76.8%, 81.2% and 79.6%, which further solving the problem of over-reliance on expert experience. It is also applied to the example analysis to obtain the human factor reliability of the travel dispatcher in this scenario, and gives the highest probability of failure behavior, which provides an improvement direction for the dispatching emergency handling protocol.

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